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ABSTRACT

Elite School Designation and Housing Prices: Quasi-Experimental Evidence from Beijing, China*

We explore recent policy changes which aim to equalize access to elite elementary schools in Beijing, to identify the effect of access to quality education on house prices based on a unique dataset. Using property transaction records from Beijing over the period 2013-2016, we construct a balanced 4-wave panel of *residential complexes*, each of which linked to its designated primary schools. Whereas the *multi-school dicing* policy involves randomly assigning previously ineligible pupils to key elementary schools through lotteries, the policy of *school federation led by elite schools* consolidates ordinary primary schools through alliance with elite schools. Moreover, the designated primary school for a residential complex can change from an ordinary primary school to a key elementary school without involving neighbouring schools in surrounding residential complexes through a *"pure" re-designation* effect. We allow for systemic differences between the treated and non-treated *residential complexes* using the Matching Difference-in-Differences (MDID) approach. Our estimates indicate that the effect on house prices of being eligible to enrol in a municipal-level key primary school is about 4-6%, while the premium for being eligible for a less prestigious district-level key primary school is only about 2-3%. Our findings are robust to an alternative measure of primary school prestige based on an unofficial ranking from a popular parenting support website, which is shown to be closely related to the number of awards in academic tournaments.

JEL Classification: R21, I28, H44

Keywords: quality school designation, house price premium, Matching DID, China

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"In Beijing's overheated housing market, where schools go, money follows."
– Caixinglobal (2017)

1. Introduction

It is now well established that the quality of primary education is a key determinant of later academic achievement (Hoekstra et al. 2018). Indeed, Heckman (2011) argues that investment in early childhood education not only promotes economic efficiency, but also enhances equity at the same time. Moreover, there is growing evidence that parents value school quality when they make school choices (e.g. Koning and van der Wiel, 2013 and Burgess et al. 2015).

However, there is substantial inequality in education in China (Zhang and Kanbur, 2005), both across and within regions. The system of the so-called "key schools and universities" could date back to the early 1950s, when the People's Republic of China introduced its Five Year Plan, "in order to cultivate higher quality specialized talent for the country and rapidly promote the development of science and culture in China" (Tan and Wang 2016). However, the detrimental effect of key schools on education equity has become an increasing concern to the public and policy makers. Following the introduction of 9-year compulsory education, the authorities formally prohibited the key schools in the compulsory education stage in the 1990s. Nevertheless, parents still seem to highly value elite schools, even without the official labelling.

It has been half a century since Wallace Oates published the seminal paper on the capitalization of local property taxes on house values (Oates (1969)). Since then, a growing number of studies have contributed to the literature on school quality capitalization under different contexts in terms of countries of study, school quality measures and methodological innovations, see Ross and Yinger (1999), Gibbons and Machin (2008), Black and Machin (2011) and Nguyen-Hoang and Yinger (2011) for reviews.

In this paper, we add evidence to how school (re-)designation affects house prices across school districts, using a complex dataset we collected from three different sources. The phenomenon of steeply priced "school district houses (*xuequfang*)", i.e. properties giving access to prestigious publicly funded schools, has consistently been one of the hottest topics in the Chinese media in recent years. According to one estate agent, in 2013 house prices in Beijing's elite school districts were roughly 30 percent higher than in other districts on average (Xinhua 2016).

Using a panel data of *residential complexes* (RCs), also known as school attendance/catchment zones, derived from comprehensive data on real estate transactions in Beijing over the period 2013-2016, we investigate how house prices react to the policy changes which aim to equalize access to quality publicly-funded elementary schools. We start off by estimating the spill-over effects of public education quality on house prices in Beijing, using the hedonic price model. The results indicate that, after controlling for housing and residential features, as well as neighbourhood and location characteristics, the mean house price in key primary school catchment areas is about 6% higher than that for ordinary primary school catchment areas in the Ordinary Least Squares specification. Secondly, school attendance zone changes based on school district adjustment, multi-school dicing or pure re-designation increase the premium of municipal key primary school catchment areas, but have no effect on district-level key primary schools in the fixed-effect specifications, whether we pool the three policy changes together or consider them separately.

Furthermore, we allow for systemic differences between the treated and non-treated RCs using *Propensity Score Matching (PSM)* and account for the common trend in house price inflation using the *Difference-in-Differences (DID)* approach. Our *Matching DID (MDID)* estimates indicate that the effect on house prices of becoming eligible to enrol in a municipal-level key primary school is about 4-6%, while the premium for becoming eligible for a district-level key primary school is only about 2-3%. The price impacts of the three different channels are broadly comparable to each other. Our findings are also robust to an alternative measure of primary school prestige based on the number of awards in academic tournaments.

The remainder of the paper is structured as follows. Section 2 presents the background of the reforms in Beijing. Section 3 briefly reviews the relevant literature. Section 4 discusses the MDID methodology. Section 5 presents the data and the descriptive statistics. In Section 6, the empirical analyses are presented and discussed. Section 7 shows the sensitivity analysis. Finally, Section 8 concludes.

2. Background

A private housing market was not introduced in China until the early 1990s as part of the reform of the urban economy. Before that, most urban residents lived in housing units constructed and owned by their employers. After the housing reform, employees no longer received allocated housing and had to buy or rent from the private housing market which had grown from strength to strength (Sato (2006), and Zhang and Yi (2017)). According to Fang et al. (2015), the residential housing market as measured by residential house sales volume grew by about 15% per annum between 2002-2013.

Beijing offers an excellent case study on the education policies and housing market of China. As the Chinese capital since the founding of the People's Republic in 1949 and the nation's political, cultural and educational centre, Beijing has not only the most developed housing market in the country but also arguably the best resources of education, in particular higher education. However, competition for access to the elite schools which traditionally has excellent track records of graduate enrolment into the country's best-known universities, is exceptionally fierce and starts well before the formal entry to the public education system.

Public schools dominate all stages of education in Beijing. In theory, access to the 9-year compulsory education is free and non-selective, and based on the principle of "*attending nearby schools*", according to parental household registration (*hukou*) and house ownership (Feng and Lu (2013)).[1] This implies that securing an address in the catchment of the school district is a necessary if not sufficient condition to enrol one's kids into a so-called *key primary school (KPS)*.[2]

The system of Key Schools in China originated from the 1950s, when only a small minority of people received more than primary education. The initial focus was on creating key secondary schools in order to improve the quality of secondary and higher education. In 1962, the Ministry of Education instructed all counties and districts in cities to create (at least) one key primary school. By 1981, there were 5,271 KPS in the country, accounting for only 0.6% of all primary schools (Tan and Wang 2016). These elite schools served the purpose of a model for pupils and teachers in local ordinary schools and sometimes showcases of New China's educational achievement to the foreign visitors in the pre-reform era.

A KPS has substantially better education quality compared to an ordinary primary school. In general, a KPS has higher per capita funding, better teacher quality, and highly favourable student socio-economic backgrounds, all contributing to the students' superior academic attainment. In 2013, 39.6% of students attended a KPS in Beijing in our sample, while this ratio increased by almost 7 percentage points (or 17%) to 46.5% in 2016.

With an aim of equalizing access to elite schools, the primary schools are no longer officially ranked by the local government in Beijing since 2000s. However, we can still classify current primary schools into key or ordinary schools on the basis of historical records. Within key primary schools, one can further distinguish between two classes in ascending order of prestige: district-level or municipal-level. While our main analysis is based on the objective historical ranking of schools, in the sensitivity analysis we will test the robustness of our result using an alternative school

[1] *Hukou* is effectively a household registration system in China which intends to reserve access to education, health care, employment and welfare to the holders of local *hukou*, see Wang (2005).

[2] You (2006) provides a review of the *key school system* in basic education in China.

classification obtained from a popular parenting support website which collects subjective rankings of parents regarding the performance of schools.[3] While these are not official rankings, they show strong consistency and very high correlation with the objective historical quality measures.

There is no standardized test at the primary school level. Indeed, no performance statistics at all are publicly available for the compulsory education stage which comprises primary education. This means that we are unable to provide direct measures of academic success by types of schools. However, we are able to show that the classification of school types we use are closely related to the number of awards in the prestigious municipal-level academic tournaments over the sample period.[4] The medals are designed to honour students for outstanding achievements at exams, sports, art activities, and national or international science competitions by the municipal government of Beijing.[5] A higher number of medals indicates better education quality of school and serves as a strong signal to parents when choosing a school.

Table 1 describes the number of awards gained before 2016 by school type in Beijing. It clearly shows that most of the awards are obtained by key primary schools, especially the more prestigious municipal key primary schools. We interpret this as strong evidence that the performance of key schools is much stronger than Ordinary schools. The small number of ordinary schools with superb achievements in terms of academic tournament awards reflects the fact that the school classification is based on pre-2000 records. In the sensitivity analysis we will explore a subjective but more up-to-date classification.

Table 1: Quality of schools

Number of awards	Ordinary	District KPS	Municipal KPS	Total
0	2,404	832	282	3,518
1	20	40	36	96
2	0	0	12	12
3	0	12	8	20
4	14	22	38	74
5	0	0	14	14
6+	18	0	62	80
Total	2,456	906	452	3,814

Notes: The awards include total numbers of Gold and Silver medals.[6]

[3] http://www.jzb.com/bbs/bj/

[4] Chan et al. (2018) also uses tournament performance as a quality indicator for primary schools in Shanghai.

[5] The official procedure is to submit the application to the municipal government and then the awards are decided after the judgement by the officers from the government

[6] http://jw.beijing.gov.cn/xxgk/zxxxgk/201805/t20180523_50452.html.

School catchment areas in Beijing are regularly reviewed and adjusted. Shortly before the start of every school year, the admissions booklets of each primary school will indicate which residential complex (RC) belongs to its catchment area. While the catchment area and any policy regime it belongs to can be derived from the websites of the school and relevant District Education Authorities, there is no central register which documents the changes of the school districts, leading to difficulties in data collection. In practice, we firstly find the annual admissions booklets of all primary schools which document the detailed admissions policy over the period 2013-2016, and link with the corresponding RCs manually.

Any changes in the school districts are regulated by the municipal government in Beijing, which consists of 12 districts. It is worth noting that the (re-)designation of schools might not be random in practice, as the decision-making process of the government is effectively a black box to researchers. Although the municipal government of Beijing has a clear aim to reduce the education inequality, the district governments have discretions in the way the policy is implemented, especially regarding the specific channels. Importantly, we expect school re-designation to be unexpected event to the residents until local government discloses the admissions booklets only a few weeks before the start of the school year.

A number of education policies recently enacted by the municipal government in Beijing are designed to reduce inequality in education. The ***multi-school dicing*** policy involves randomly assigning previously ineligible pupils to (historical) key elementary schools through lotteries, which breaks up the traditional correspondence between a specific RC and a specific primary school. The idea is to allow key schools to cover larger areas than before. Pupils who fail to win the lottery for the elite school can still be allocated to other schools nearby.

In contrast, the ***school federation led by elite schools*** policy attempts to consolidate low quality schools through alliance with existing elite schools. By pooling resources and improving school governance, pupils enrolled in ordinary schools can expect to partially access the benefits associated with direct enrolment in a key school.

Moreover, a residential complex can also experience which we label a ***"pure" re-designation***, if the designated school is changed from an ordinary school to a key primary school.

Conceptually, these policies can be regarded as representing the three different approaches to improve school access and quality in terms of governance theory, i.e. markets, networks and hierarchy (Greany and Higham 2018). The market-oriented ***multi-school dicing*** policy focuses on facilitating parental choice which may in turn encourage schools to compete for pupils through increased quality. In contrast, the ***school federation*** approach relies on the creation of networks of "local clusters" that enable the high-status school to share resources and "best practices" with ordinary schools. Finally, the ***"pure" re-designation*** channel might be interpreted as working through the administrative mechanism. However, it is also important to note that adopting either multi-school dicing or school federation does not necessarily mean access to better schools.

In the absence of better data which would allow us to model the determinants of various policy options, it is simply not possible to fully disentangle the causes for the variations in the treatment effects. Nevertheless, it is interesting from the perspectives of both the public and policy makers to understand the heterogenous treatment effects by policy options, which in turn might motivate future research or even future policy design.

3. Literature

A large literature has been devoted to the effect of school quality on house prices, in general finding support to the Tiebout model which predicts residential sorting (Tiebout (1956)). Ross and Yinger (1999), Gibbons ad Machin (2008), Black and Machin (2011) and Nguyen-Hoang and Yinger (2011) offer excellent reviews. While earlier studies are largely descriptive, recent ones strive to uncover the causal relationship, which is extremely important for policy designs, using the quasi-experimental framework.

Traditional hedonic pricing model estimates of the school quality effect are likely to suffer from omitted variable bias or endogeneity problems. Black (1999) first applies the *regression discontinuity design (RDD)* using administrative boundaries, also known as the b*oundary discontinuity design (BDD)* approach, in an attempt to net out time-invariant unobserved neighbourhood fixed-effects which are correlated with school quality. Following their study, many recent papers have examined the relationship between school choice and property values (Fack and Grenet. 2010; Gibbons et al. 2013; Schwartz et al. 2014; Agarwar et al. 2016).[7]

Apart from the link between school quality and house prices, recent papers have focused on how the presence of prestigious schools affect the house segmentation and the effect of school designation on house prices across countries, from the perspective of residential sorting. Brunner et al. (2012) provide the first direct empirical evidence as to how designating educational resources affect residential sorting and house prices in the U.S. By exploiting a policy change which allowed

[7] Gibbons et al. (2013) further develop the RDD approach using matching. Compared to the OLS baselines, they all find a smaller capitalization effect, at below 4% for a one standard deviation increase in test scores.

the inter-district transfer, they argue that the introduction of inter-district choice program drove relatively high-income household to move to lower-quality districts with lower housing prices. Lee (2015) exploits a reform in Seoul which randomly relocated better performance schools from city centre to city periphery to evaluate the prices change, suggesting that residential land prices rose by about 13% on average in the better school district. Chung (2015) also exploits the reform in Seoul which allows students to choose school within and outside the district. After the school choice reform, the residential prices in previously high performing school districts fall by around 10-27% relative to low-performing districts. Machin and Salvanes (2016) evaluate the effects of altering the policy from the enrolment to the nearest school to open enrolment in Oslo in 1997. Their results suggest that parents value school quality significantly and house prices change with the value of schools. By exploiting two reforms in Chicago which increased the probability of admission for students living nearby a magnet elementary school, Bonilla-Mejia et al. (2018) show that house prices increase significantly with the probability of enrolling in a better school.

Moreover, there is a heated debate regarding the controversial school performance table, sometimes known as the league table. Empirical studies have suggested that information on school's performance can significantly affect parent's choice. Allen and Burgess (2013) also suggest that a performance table is valuable for helping parents choose the right school and can help student achieve better academic performance compared to randomly picked school from the choice set. Burgess et al. (2015) show that the majority of households in the UK have strong preference on academic performance of schools.[8] Based on a boundary discontinuity design, Harjunen et al. (2018) demonstrate that one standard deviation increase in average test scores pushes up house prices by 2.5% in Helsinki.

To the best of our knowledge, only few studies have explored the impact of elite school designation on house prices in the context of China. Feng and Lu (2013) is the only causal study of the effect of school quality on house prices in China published in English. Using a DID approach, they find that the re-designation of a previously ordinary high school to a specific high-quality school status increases the house price in its residential area by 6.9% in Shanghai. However, to the extent that school designation policy by the municipal government is not entirely exogenous, e.g. due to concerns for equal access across geographical areas (e.g. districts), one cannot rule out the possibility of endogeneity bias in the DID estimates.[9]

[8] Using a unique linked dataset, they argue that parents value the performance of schools, socio-economic composition of schools and proximity to the home.

[9] In a recent working paper, Chan et al. (2018) provide partial evidence that prices of houses with access to better

Using a unique dataset we construct ourselves, we contribute to the literature on the impact of better quality primary schools on housing prices, by being one of the few such studies in the Chinese context. By employing a number of econometric methods such as fixed-effects, differences-in-differences and matching DID, and using alternative school quality measures, we find strong causal evidence that access to quality schools significantly increases housing prices. While our results are consistent with literature, we go further by comparing different policy options which aim to improve access to key primary schools, which show surprisingly similar and robust effects on housing prices. Moreover, access to the more prestigious municipal-level key primary schools leads to much higher price premiums, regardless of the treatment type.

4. Methodology

This study employs a quasi-experimental research design to examine three recent educational policy reforms in Beijing which aim to widen access to quality education for all. Conventional multivariate regression analysis is unlikely to uncover the true causal effect of the treatment due to omitted variable bias and endogeneity or self-selection in the treatment (see e.g. Rubin (1974) and Blundell and Diaz (2009)).

To the extent that the treatment status is randomly assigned, a conventional DID estimator would suffice to uncover the true causal effect with the help of a well-defined control group which is assumed to share the common trend. Following the literature, we choose the semi-log specification:

(1) $$\ln price_{it} = \beta_0 + \beta_1 keysch_i + \sum \beta_i X_i + \varepsilon_{it}$$

where $lnprice_{it}$ is the logarithm of mean house price of residential complex i in year t, *keysch* is a dummy for the key school status of the designated primary school (alternatively we use two dummies to distinguish between district and municipal-level key schools), $\mathbf{X}_i$'s are control variables, ε_{it} is the error term, and β_0, β_1, and β_i's are coefficients.

To account for the time trend, we first employ a simple DID strategy. In this setting, we need the Conditional Independence Assumption to hold in the first difference equation. Then, the simple DID setting is below:

(2) $$Y_{it} = a + \sum_{2013}^{2016} year_i + Keysch_{it} + \sum_{2013}^{2016} year_i * Keysch_{it} + X_{it} + \varepsilon_{it}$$

schools are 13% higher by examining the school re-designation policy in Shanghai. While they apply the boundary fixed-effect on household transaction data, they are unable to control for neighbourhood fixed-effect.

where $year_i$ denotes years between 2013 and 2016. The interacted term is our variable of interest which captures the price premium for being designated as a key primary school. In a simple DID, the effect can be identified if the below condition is satisfied:

(3) $$E\left(Y_{0,t} - Y_{0,t'} \middle| X, Keysch = 0\right) = E(Y_{0,t} - Y_{0,t'} | X, Keysch = 1)$$

where Y_0 denotes the potential outcome in the absence of the treatment, which is unobservable for the treatment group. Similarly, Y_1 denotes the potential outcome in the presence of the treatment.

However, there are good reasons to believe that the assignment of the treatment status by policy makers in our case is non-random. For example, the government might encourage the creation of *school federations* of non-KPS's in certain areas led by existing elite schools to improve the access to elite education geographically. [10] In other words, the *non-ignorable treatment assignment assumption* required for unbiased DID estimates is not satisfied. To deal with this issue, we will use *Propensity Score Matching (PSM)* to achieve data balance such that DID can yield unbiased estimates on the matched data. It is expected that the RCs with and without experiencing a change in KPS status in the designated school are much similar in many aspects after the matching. In practice, we will use two alternative matching strategies to ensure that there are no systemic differences between the treatment and control groups (Guo and Fraser (2010)). The strategies are defined by propensity scores estimation using logistic regressions method with either Mahalanobis distance or nearest neighbour within caliper. The variables used for matching include fixed characteristics of residential complexes, including service charges, level of facilities, distance to hospital, distance to city centre, and distance to business centre. The characteristics are time-invariant and belong to historical information. Given the assumption of "Strong Ignorability" proposed by Rosenbaum and Robin (1985), $0<P(Keysch=1|X)<1$. Together with the previous two equations, that implies the following,

(4) $$(Y_0, Y_1) \perp D \mid P(X)$$

Together with the index sufficiency and the simple DID, the MDID condition becomes:

(5) $$E\left(Y_{0,t} - Y_{0,t'} \middle| P(Z), Keysch = 0\right) = E(Y_{0,t} - Y_{0,t'} | P(Z), Keysch = 1)$$

4.1 Channels

[10] In an education journal in Chinese, Ha and Yu (2017) present evidence on the price premium of previously non-key primary school catchment areas which were integrated into school federations led by elite schools in Beijing. They find a modest 1.2% effect on average. While they attempt to apply two-way fixed effect and boundary discontinuity design, they do not account for the non-random assignment of the reformed schools.

During our sample period 2013-2016, there were three possible ways in which the designated primary school of a *residential complex* (RC) could change from an ordinary primary school to a KPS. Apart from *multi-school dicing* and *school federation*, an RC previously affiliated to an ordinary primary school could be reassigned a KPS through *"pure" re-designation*, a change which does not involve any neighbouring schools. In principle, these three channels can affect the house price differently due to the different nature of the distribution of resources.

The *multi-school dicing* policy reduces education inequality by distributing the educational resources by lotteries. However, people who are risk averse may not be willing to buy a property which cannot guarantee their children a place at a KPS. On the other hand, the *school federation* redistributes the education resources throughout all the schools in the alliance.[11] In reality, people may doubt how much resources would be redistributed from the leading elite school to the low-quality schools. This in turn will affect their willingness to pay for the property. In contrast, the *"pure" re-designation* mechanism offers a neat identification of the effect of quality school designation, as it does not involve any other RCs or schools. Therefore, we will examine potential heterogeneous treatment effects by comparing each of the three treatments to the same control group separately in our analysis,

It is often argued that private schools provide an alternative to good quality education in the state sector. In this paper, we allow for the interaction of number of independent schools (within a 10km radius) with the key variables of interest in the regressions.

5. Data

There is no publicly available dataset to evaluate the price premium of quality schools in China. In this study, we created a unique dataset from three different sources, which contain detailed information in relation to the individual property transactions, school districts, and school characteristics. The final data consists of a 4-wave balanced panel of residential complexes (*xiaoqu*) in the 12 urban districts in Beijing over the period 2013-2016.[12] An RC is the urban equivalent of a village and serves as the most fundamental organization unit for the urban population in China. Each RC has its own neighbourhood or residents' committee. In Chinese megacities like Beijing, an RC usually contains hundreds of condominiums in medium or high-rise buildings within well-

[11] School-federations are similar to Teaching School Alliances (TSAs) which are promoted in the UK since 2010, with nationally designated excellent schools leading the alliance (DfE, 2010).

[12] The remaining 4 districts where data is unavailable are all rural suburbs, and far away from the Central Business District (CBD).

defined boundaries of one designated publicly funded primary school where the kids are enrolled (Zhang and Yi (2017)).

We first use data harvesting techniques to collect detailed information on all transactions of second-hand properties over the period 2013-2016 from the two leading property websites *Fang.com* (http://www.fang.com/) and *Lianjia.com* (https://www.lianjia.com/).[13] From these, we derive the annual mean transaction prices as well as time-invariant key characteristics for each RC. Second, using Google Maps, we construct the geographic information, including distance of each RC to the city centre proxied by the Central Business District (CBD), the nearest subway station, the nearest top-grade hospital, and the number of independent schools within a 10-kilometre radius. The third source of the dataset involves manually matching RCs to the designated schools and the relevant school status and any regime changes during the sample period, using school admissions booklets or the websites of the district education authorities.[14]

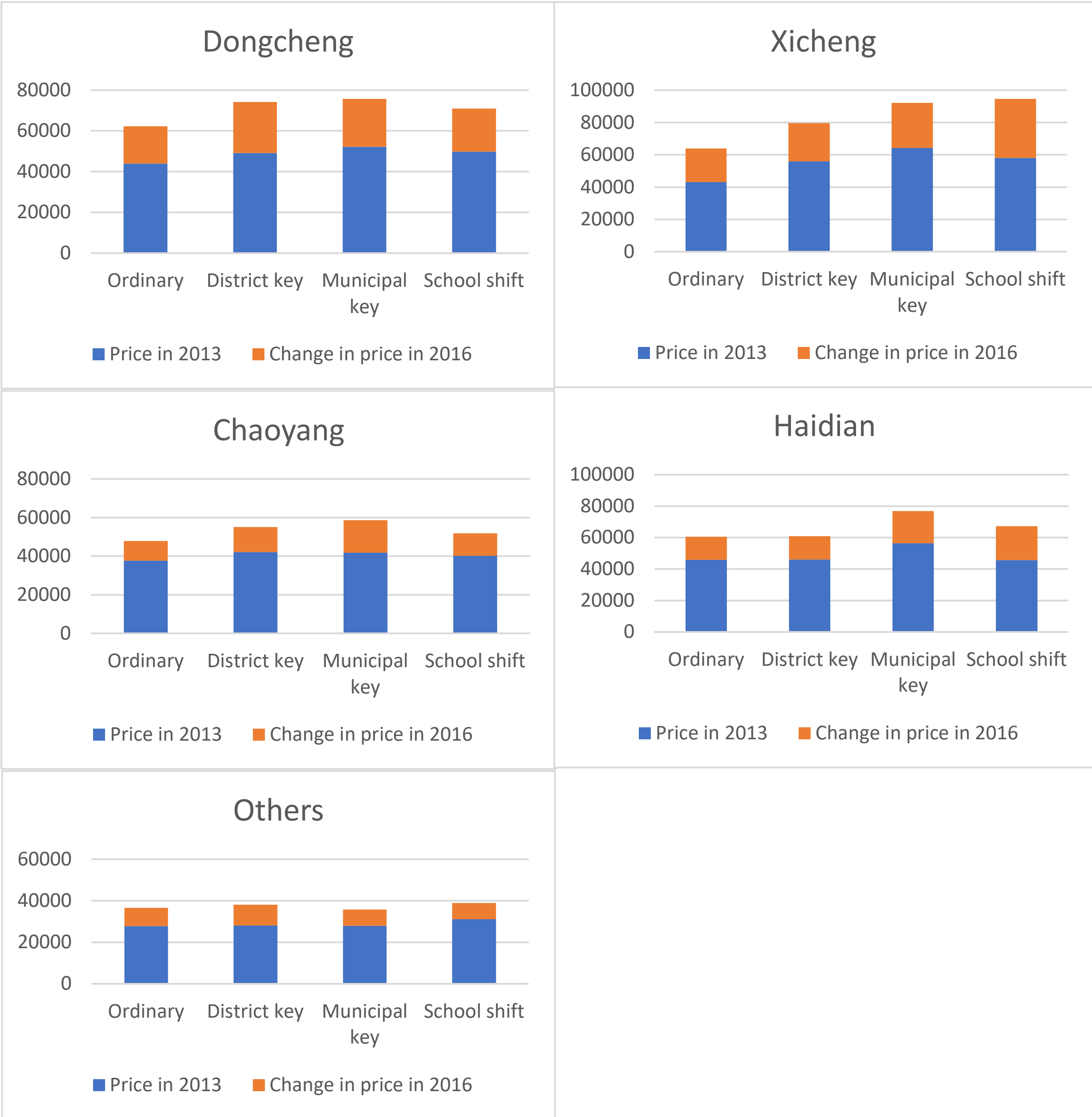
We exclude RCs with too few transactions in any year in the sample period, or with missing values on key variables. To ensure our results are not driven by outliers in the outcome measure of mean real price per square metre (in RMB yuan), we also drop the top and bottom 1% of the mean price distribution. Moreover, we also realize that a handful of RCs have experienced change of designated school status from district-level KPS to municipal-level KPS during our sample period, due to school reassignment. Since our interest is to estimate the treatment effect of being assigned a KPS, it is natural to drop those RCs which have experienced further improvements. The final sample is a balanced panel of 1,907 RCs, each observed in all 4 years over the period 2013-2016. Given that the unit of observation in our sample is an RC-year combination, we report standard errors clustered at the RC level in all regressions.

Figure 1 show the mean real house prices in the base year 2013 and the price increases over the 2013-2016 period, by districts and policy regime transition type. As expected, the four districts in Central Beijing have much higher house prices than the peripheral districts. Moreover, within each district, there are significant house price premia for RCs attached to elite primary schools. However, it is often RCs that experienced school status upgrading that have the highest increases in house prices (at least in relative terms), in the sample period.

[13] Jointly they cover virtually all "used (second-hand)-property" transactions in Beijing.

[14] As no official primary school ranking in Beijing is available after 2000, we exclude all new primary schools with missing school status information in the main analysis.

Figure 1: House prices by districts and transition type



Note: *Ordinary* indicates ordinary school in both years; *District Key* indicates district-level key school; *Municipal Key* indicates municipal-level key school; *School shift* indicates changing status from ordinary to any type of key school. The solid bars represent the house prices in 2013 while the dashed bars denote the price changes between 2013 and 2016. All prices and changes are measured in 2013 constant prices.

Table 2 shows the frequencies of RCs by treatment status (i.e. whether their designated primary school has changed from ordinary to key school status over the sample period), and if being treated, by the treatment types. Of the 1907 RCs, 139 (7.3%) RCs have experienced a change in the school status over the sample period, while 1,768 (92.7%) RCs remain in the control group of ordinary primary schools. In terms of the various forms of treatment, 28 RCs have undertaken multi-school dicing, 15 RCs have undertaken school federation and the remaining 96 RCs are accounted for by the "pure" re-designation. It is worth noting that adopting either multi-school dicing or school federation does not necessarily mean access to better schools. Indeed, only around half of the schools of undertaking multi-school dicing and one quarter of schools undertaking school federation policies in our sample period are treated, i.e. get access to key primary schools.

Table 2: Residential complexes by treatment types

Whether Change from ordinary to key school during 2013-16:	No School federation		School federation		Total
	No Multi-school dicing	Multi-school dicing	No Multi-school dicing	Multi-school dicing	
No change (Control)	1,701	26	41	-	1,768
Change (treatment)	96	28	15	-	139
Total	1797	54	56	-	1,907

One key identifying assumption for the DID approach is that the treatment and control group share a common time trend in the absence of the treatment, i.e. in the pre-treatment period. Our 4-wave balanced panel allows us to test this in an informal way, by plotting mean real housing prices by treatment type. Figure 2 shows that RCs exposed to either district or municipal key school re-designation have the same pre-treatment time trend, relative to the omitted control group of RCs which have not experienced a school re-designation throughout the sample period. It is only after being treated at period 0, that the treated group enjoy higher increases in housing prices, with disproportionate increases for municipal-level key schools.[15]

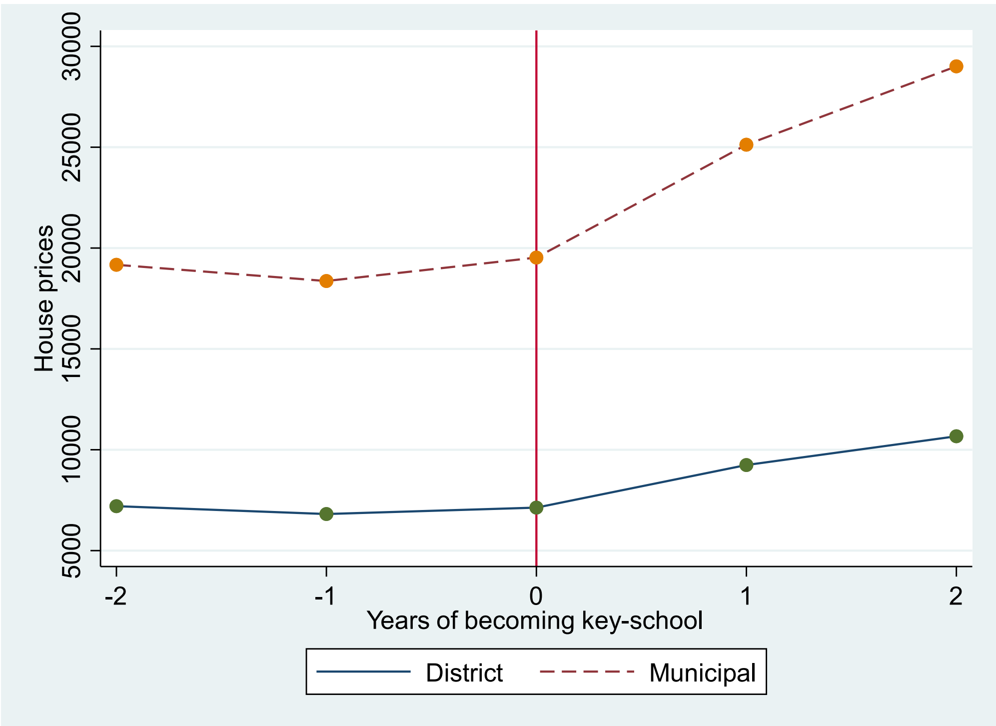
Figure 3 shows the corresponding time trend, by treatment type. Because of small cell sizes, the graph only shows mean real housing prices from the year immediately before the school status change. Again, all 3 treatment types have the same pre-treatment time trend, relative to the omitted control group of RCs which have experienced no change in school status. Figure 2 and 3 also suggest that the selection of RCs re-designation policy is unlikely to be random across channels. It might be

[15] Figure A1 in the Appendix confirms the pre-treatment time trend remains the same, even after we exclude all pre-existing KPS from the control group.

because the educational resources are unevenly distributed in the city and the inner districts with higher housing prices have higher chance of re-designating to better schools.

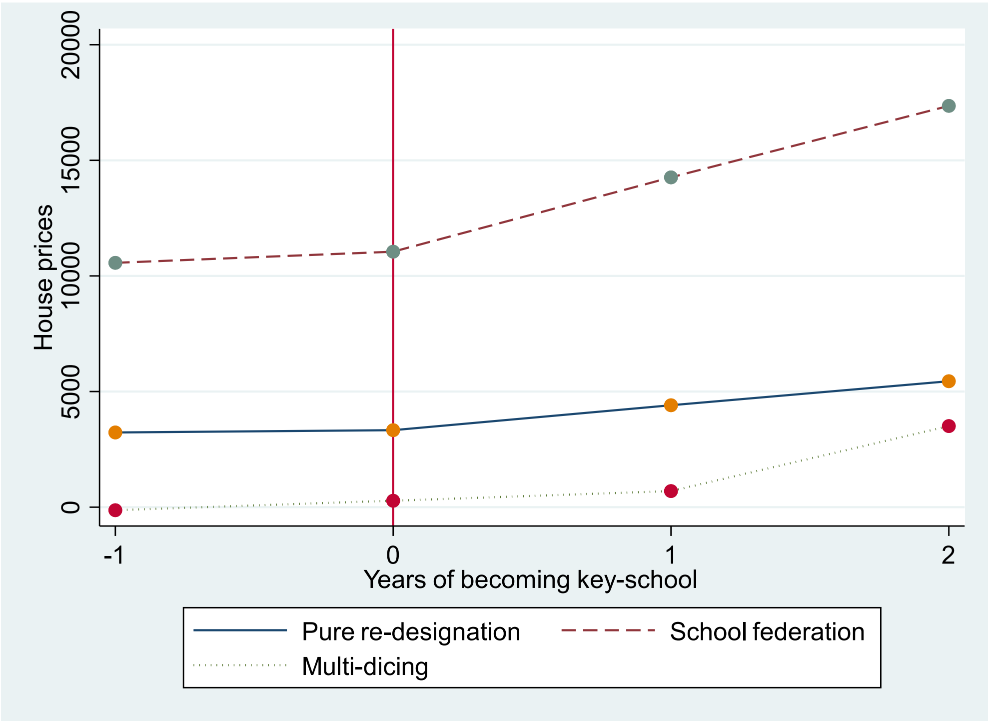
Table A1 in the Appendix shows the results of running a treatment dummy on baseline (2013) RC characteristics for the full sample, and by treatment type. It turns out that that none of the RC characteristics are significant determinants of the treatment status or type. On the other hand, the distance variables, and in particular, the district dummies, seem to matter. We interpret this as suggestive evidence that the choice of the treatment type (mechanisms) might reflect the preferences of the local education authorities in different districts.

Figure 2: Trend of real house prices by treatment status and KPS level



Notes: The vertical axis shows the real price premiums of the treated group by key school level, relative to the control group of all RCs with no change in KPS status over time.

Figure 3: Trend of real house prices by treatment type



Notes: The vertical axis shows the real price premiums by treatment type, relative to the control group of all RCs with no change in KPS status over time. Too few observations for two years before treatment taking place.

Table 3: Descriptive statistics, analytical sample

	2013	2014	2015	2016
Price per m^2 (dependent variable)	37,707	36,994	38,184	50,657
School characteristics:				
Key Primary School	0.396	0.437	0.463	0.465
District-level Key Primary School	0.269	0.296	0.318	0.319
Municipal-level Key Primary School	0.127	0.141	0.145	0.146
Control variables:				
# independent schools (within 10km)	6.984			
Greening rate	0.332			
Mean floor area ratio	2,542			
Service charges	1.575			
# floors	12.27			
Mean floor area per flat (m^2)	85.54			
Distance to City Centre (km)	12.275			
Distance to nearest top-grade hospital (km)	2.437			
Distance to nearest subway station (km)	1.009			
Year of construction	2000			
Local amenities	3.995			
Observation	1,907	1,907	1,907	1,907

Note: Price in RMB yuan in 2013 constant price.

Table 3 presents the descriptive statistics for the analytical sample by calendar year. All house prices have been converted to constant 2013 prices using the Consumer Price Index (CPI) for Beijing. The mean real house price in Beijing grows from 37707 RMB yuan (USD 5976) in 2013, to 50657 yuan (USD 8028) in 2016, an increase of 34.3% in real terms over 3 years.[16] Over the 3-year sample period, 6.9% of RCs experienced a positive change in the status of the designated primary school. While 39.6% of all residential complexes are in the school district (SD) of a Key primary school in 2013, two thirds of which are district-level KPS, the share of elite SDs grows to 46.0% in 2016, with increases in both the district-level and municipal-level key schools.

All control variables except for years since construction are time-invariant. There are on average 7.0 independent schools within a 10km radius of the RC. The mean greening rate of 0.332 indicates that the green areas account for almost one-third of the land surface of the residential complex. The floor area ratio is the ratio of total construction area to the land area. The average service charge is 1.575 RMB yuan (0.27 USD) a month per square metre. The mean number of floors is 12.3, reflecting the fact that is Beijing is very densely populated metropolis. The mean floor area per flat is 85.8m^2, while the average year of construction is 2000 in 2013. The straight-line distances to the city centre and the nearest top-grade hospital are 12.3 and 2.4 km's respectively, while the distance to the nearest subway station is only 1.0 km. The average number of local amenities such as banks, post offices and supermarkets, is 4.0.

Table 4 describes the characteristics of residential complex across districts, especially the density of key schools. In Beijing, there are 12 districts. Districts with fewer observations are grouped into one category. In the Table, Haidian has the highest concentration of key schools amongst the regions in Beijing. The Dongcheng and the Xicheng District are the centre of the city and also have more key schools compared to other regions of the city. Over the sample period, there is a significant increase in the coverage of key schools, especially the district key schools.

[16] The year-end exchange rates between USD and CNY are 6.152, 6.158, 6.284 and 6.643 for 2013, 2014, 2015 and 2016 respectively. We use the mean of 6.31 over the period to derive the USD equivalents.

Table 4: Density of school quality across regions

Regions	Dongcheng	Chaoyang	Haidian	Xicheng	Others
2013					
House price	47,612	39,859	49,809	55,457	27,912
Ordinary	0.569	0.623	0.294	0.463	0.814
District KPS	0.174	0.315	0.335	0.262	0.160
Municipal KPS	0.257	0.062	0.371	0.275	0.026
2016					
House price	68,732	51,662	67,106	80,765	36,912
Ordinary	0.422	0.446	0.243	0.302	0.749
District KPS	0.193	0.463	0.371	0.309	0.216
Municipal KPS	0.385	0.091	0.385	0.389	0.035
# independent schools	7.45	9.17	9.54	8.17	4.47
Mean floor area per flat	71.36	87.88	87.26	72.58	88.63
Number of awards per RC	0.018	0.345	1.338	0.503	0.008

Note: Price in RMB yuan in 2013 constant price. The awards include both Gold and Silver medals in prestigious academic tournaments in 2016.

6. Empirical Results

Table 5 presents the pooled OLS and FE (fixed-effect) estimates as well as the corresponding DID estimates, without and with the breakdown of the elite schools into district or municipal-level. These will form the benchmark against which the MDID results are compared. Note that in all specifications we include district dummies and full interaction of number of independent schools with the variable of interest. This is important, given that Figure 1 suggests that there is significant heterogeneity across districts in the initial house prices by transition status. We also include year dummies to allow time-varying treatment effects (Bertrand et al. 2004).

Column 1 shows that the regression adjusted price premium of access to a key primary school is 5.9%. When we distinguish between district and municipal-level key primary schools in column 2, we find that the price premium for the more prestigious municipal-level key school is much higher than its district-level counterpart, at 14.1% and 3.0% respectively, both statistically significant at the 1% level. Columns 3 and 4 report the corresponding FE estimates which rely on RCs with re-designation of schools for identification. Whereas there is still a positively significant premium for municipal-level KPS of 5.2%, the effect for district-level KPS is negative but only significant at the 10% level. Therefore, the price premium of an elite school is driven by the change to a municipal-level key school. The last two columns of Table 5 present the DID estimates. This time the re-designation as an elite school increase house prices by 1.9% and 4.3% for district and municipal KPS respectively, both statistically significant at the 1% level. Note that the estimated time effect for 2016, the end year of the sample period, is remarkably consistent across all specifications, within the range of 0.276-0.292. These correspond to an increase in real house prices of approximately 31.8% - 33.9% over three years.

Table 6 shows the FE results by treatment type. In each subgroup, we only compare the relevant treatment group to the common control group which is not affected by any of the reforms. The first two columns show the effect of multi school-dicing, which is a modest 3.2% and only significant at the 10% level. When we distinguish between district and municipal KPS, only the latter has a significant price premium of 5.5%. The next two columns show that there is a 10.0% increase in price premium for school federation, but only if it involves a municipal KPS. The last two columns include the results for the "pure" re-designation effect, which is statistically insignificant overall. However, when we distinguish between the two tiers of elite schools, being re-designated as the more prestigious municipal KPS carries a marginally significant 3.0% price premium while being upgraded to a district-level KPS has no significant effect. Presumably this difference partly reflects the difference in the teaching quality and resources of the two types of key schools.

Table 5: Effect of school designation on house prices (OLS, FE, DID)

	OLS		FE		DID	
	(1)	(2)	(3)	(4)	(5)	(6)
KPS	0.0588***		0.00292		0.0522***	
	(0.00726)		(0.00734)		(0.00728)	
KPS*After-reform					0.0264***	
					(0.00537)	
DKPS *After-reform						0.0192***
						(0.00616)
MKPS *After-reform						0.0432***
						(0.00648)
District KPS (DKPS)		0.0304***		-0.0142*		0.0257***
		(0.00771)		(0.00762)		(0.00768)
Municipal KPS (MKPS)		0.141***		0.0524***		0.130***
		(0.0120)		(0.0143)		(0.0121)
2014	-0.0163***	-0.0166***	-0.0139***	-0.0142***	-0.0160***	-0.0163***
	(0.00222)	(0.00224)	(0.00221)	(0.00222)	(0.00222)	(0.00223)
2015	0.00440*	0.00433*	0.00793***	0.00789***	0.00484**	0.00476**
	(0.00231)	(0.00230)	(0.00232)	(0.00232)	(0.00230)	(0.00229)
2016	0.288***	0.288***	0.292***	0.292***	0.277***	0.276***
	(0.00329)	(0.00329)	(0.00334)	(0.00334)	(0.00433)	(0.00433)
# independent schools (within 10km)	0.0148***	0.0143***			0.0148***	0.0143***
	(0.00153)	(0.00151)			(0.00153)	(0.00151)
Greening rate	0.203***	0.209***			0.204***	0.210***
	(0.0599)	(0.0583)			(0.0599)	(0.0583)
Mean floor area ratio	-0.00936***	-0.00905***			-0.00937***	-0.00905***
	(0.00277)	(0.00256)			(0.00277)	(0.00256)
Service charges	0.0378***	0.0378***			0.0378***	0.0379***
	(0.00571)	(0.00579)			(0.00571)	(0.00579)
Mean floor area per flat	-0.000416**	-0.000422**			-0.000417**	-0.000423**
	(0.000190)	(0.000188)			(0.000190)	(0.000188)
# floors	-0.00207***	-0.00174**			-0.00206***	-0.00173**
	(0.000723)	(0.000710)			(0.000723)	(0.000710)
# Local amenities	0.0997***	0.108***			0.0999***	0.108***
	(0.0143)	(0.0198)			(0.0144)	(0.0199)
Distance to City Centre	-0.0173***	-0.0171***			-0.0173***	-0.0171***
	(0.000672)	(0.000656)			(0.000672)	(0.000656)
Dist. to nearest top-grade hospital	-0.0234***	-0.0242***			-0.0234***	-0.0242***
	(0.00288)	(0.00285)			(0.00287)	(0.00285)
Dist. to nearest subway station	-0.0261***	-0.0268***			-0.0261***	-0.0268***
	(0.00533)	(0.00526)			(0.00533)	(0.00526)
Dist. to nearest subway station sq.	0.00382***	0.00388***			0.00382***	0.00388***
	(0.000394)	(0.000377)			(0.000394)	(0.000376)
Chaoyang District	-0.147***	-0.124***			-0.147***	-0.124***
	(0.0165)	(0.0164)			(0.0165)	(0.0164)
Haidian District	0.0919***	0.0902***			0.0920***	0.0905***
	(0.0182)	(0.0174)			(0.0182)	(0.0174)
Xicheng District	0.131***	0.130***			0.131***	0.130***
	(0.0203)	(0.0193)			(0.0203)	(0.0193)
Other districts	-0.255***	-0.235***			-0.255***	-0.235***
	(0.0171)	(0.0170)			(0.0171)	(0.0170)
Observations (RC-years)	7,628	7,628	7,628	7,628	7,628	7,628
R^2	0.802	0.810	0.778	0.779	0.802	0.810

Note: Standard errors clustered at RC level in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% respectively. DKPS and MKPS indicate district and municipal-level key primary schools. Omitted district is Dongcheng District.

Table 6: Fixed Effect by type of treatment

	Multi-school dicing		School federation		"pure" re-designation	
	(1)	(2)	(3)	(4)	(5)	(6)
KPS	0.0316*		0.0131		-0.00264	
	(0.0185)		(0.0241)		(0.00759)	
District KPS		0.0160		-0.0539***		-0.0106
		(0.0248)		(0.0194)		(0.00814)
Municipal KPS		0.0550**		0.0999***		0.0302*
		(0.0234)		(0.0275)		(0.0160)
2014	-0.0122***	-0.0123***	-0.0125***	-0.0125***	-0.0134***	-0.0135***
	(0.00234)	(0.00234)	(0.00235)	(0.00235)	(0.00228)	(0.00228)
2015	0.00716***	0.00717***	0.00767***	0.00765***	0.00724***	0.00724***
	(0.00239)	(0.00238)	(0.00239)	(0.00239)	(0.00236)	(0.00237)
2016	0.292***	0.292***	0.291***	0.291***	0.291***	0.291***
	(0.00348)	(0.00348)	(0.00347)	(0.00347)	(0.00342)	(0.00342)
Observations (RC-years)	6,864	6,864	6,916	6,916	7,188	7,188
R^2	0.775	0.775	0.774	0.775	0.778	0.778

Note: Standard errors clustered at RC level in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% respectively. Same controls as in Table 5.

Table 7 presents DID results in treatment type with similar setting as for Table 5. Compared to the OLS and FE results, the magnitudes of DID estimates for municipal key primary schools are marginally smaller, at around 4% for all subgroups, but still statistically significant at the 1% level. For district key primary schools, the price premia are also statistically significant for all subgroups, but only half in magnitude at round 2%.

Table 7: DID by type of treatment

	Multi-school dicing		School federation		"pure" re-designation	
	(1)	(2)	(3)	(4)	(5)	(6)
KPS	0.0782***		0.0632***		0.0605***	
	(0.00817)		(0.00803)		(0.00764)	
KPS*After-reform	0.0273***		0.0275***		0.0251***	
	(0.00555)		(0.00556)		(0.00545)	
District KPS		0.0354***		0.0338***		0.0331***
		(0.00847)		(0.00844)		(0.00806)
Municipal KPS		0.148***		0.150***		0.142***
		(0.0136)		(0.0134)		(0.0131)
District KPS*After-reform		0.0210***		0.0195***		0.0188***
		(0.00650)		(0.00650)		(0.00625)
Municipal KPS*After-reform		0.0409***		0.0438***		0.0420***
		(0.00696)		(0.00692)		(0.00683)
2014	-0.0126***	-0.0126***	-0.0133***	-0.0135***	-0.0149***	-0.0149***
	(0.00233)	(0.00233)	(0.00234)	(0.00235)	(0.00228)	(0.00228)
2015	0.00701***	0.00707***	0.00721***	0.00687***	0.00439*	0.00470**
	(0.00238)	(0.00238)	(0.00240)	(0.00238)	(0.00234)	(0.00235)
2016	0.280***	0.280***	0.279***	0.279***	0.277***	0.277***
	(0.00434)	(0.00434)	(0.00435)	(0.00435)	(0.00433)	(0.00433)
Observations (RC-years)	6,864	6,864	6,916	6,916	7,188	7,188
R^2	0.796	0.811	0.803	0.812	0.800	0.808

Notes: Standard errors clustered at RC level in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% respectively. Control variables include all variables in the descriptive table (Table 3) and the dummies for districts, but not the interacted term between numbers of independent schools and dummy for key-school.

Table 8 shows the post-matching balancing test results for the main sample, for each of the 2 matching strategies employed. Due to the common support restriction, the matched sample is reduced by approximately 59% and 22% for Mahalanobis and Nearest Neighbour matching respectively, compared to the unmatched sample used in Table 5. For both strategies, none of the variance ratios are statistically significant at the 5% level post-matching.

Figures 4 and 5 compare the kernel densities of the propensity score between the treated and control group, before and after matching, for each of the 2 matching strategies used. The result after matching show that the matching has been successful, for both strategies.

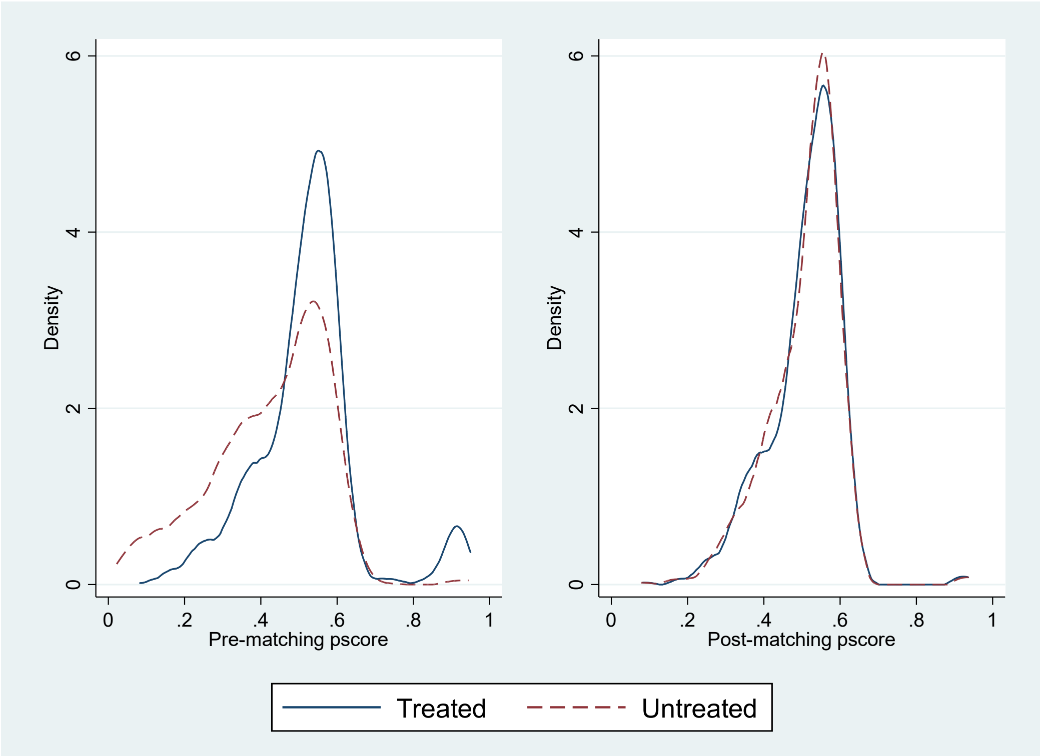
Table 8: Post-matching balancing tests

	Unmatched		
	Treatment Mean	Control Mean	Variance Ratio
Service charges	1.64	1.52	1.11
Total floor	12.54	11.98	0.99
Distance to City Centre	10.65	13.70	0.54*
Distance to nearest top-grade hospital	1.96	2.86	0.53*
Distance to nearest subway station	0.80	1.19	0.56*
Numbers of RC		1,907	

	Matched					
	Mahalanobis			Nearest neighbour		
	Treatment Mean	Control Mean	Variance Ratio	Treatment Mean	Control Mean	Variance Ratio
Service charges	1.55	1.54	1.00	1.67	1.59	1.10
Total floor	12.56	12.93	0.89	12.56	13.21	0.93
Distance to City Centre	10.56	10.51	1.02	10.93	11.21	0.80*
Distance to nearest top-grade hospital	1.95	1.96	1.04	2.01	2.05	1.15
Distance to nearest subway station	0.72	0.81	0.97	0.79	0.81	1.08
Numbers of RC		790			1,492	

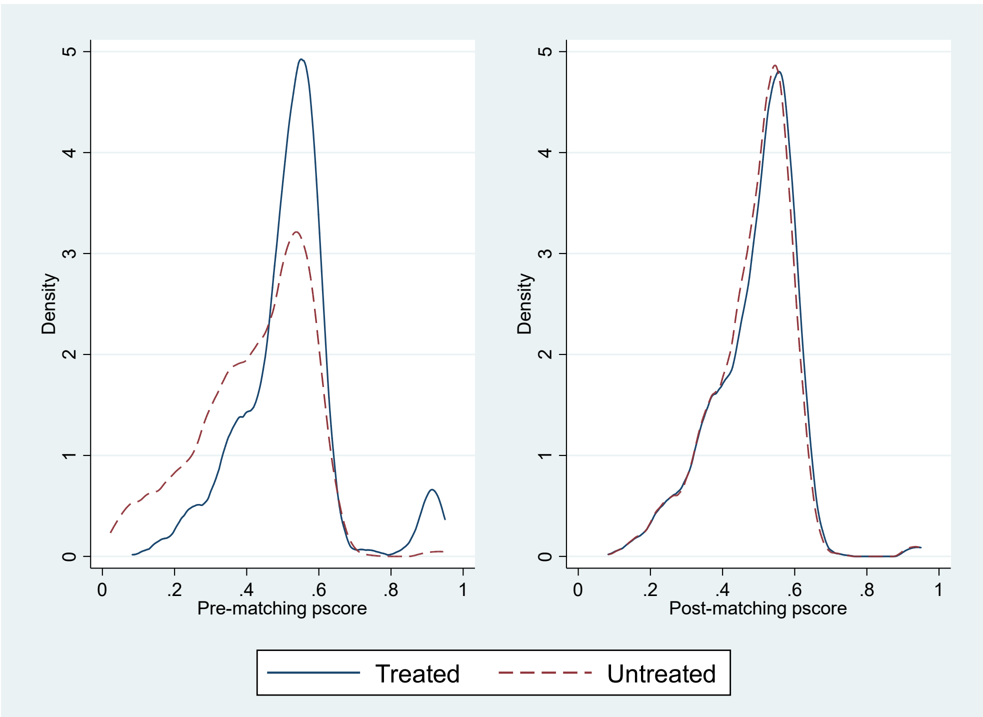
Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% respectively.

Figure 4: Comparison of kernel density of propensity scores before and after matching, school changing, Mahalanobis Metric



Notes: "Treated" and "untreated" refer to treated and untreated RCs.

Figure 5: Comparison of kernel density of propensity scores before and after matching, school changing, Logit with Nearest Neighbour



Notes: "Treated" and "untreated" refer to treated and untreated RCs.

Table 9: Matching Difference-in-differences (MDID) Estimates, alternative specifications

	Mahalanobis		Nearest neighbour	
	All			
KPS*After-reform	0.034**	-	0.034***	-
	(0.008)		(0.006)	
District KPS*After-reform	-	0.029***	-	0.027***
		(0.009)		(0.007)
Municipal KPS*After-reform	-	0.048***	-	0.049***
		(0.009)		(0.007)
R^2	0.78	0.79	0.78	0.78
Obs (RC-years)	3,160		5,968	
	Multi-school dicing			
KPS*After-reform	0.032***	-	0.038***	-
	(0.008)		(0.006)	
District KPS*After-reform	-	0.030***	-	0.031***
		(0.009)		(0.007)
Municipal KPS*After-reform	-	0.038***	-	0.051***
		(0.0010)		(0.007)
R^2	0.78	0.79	0.78	0.78
Obs (RC-years)	2,944		5,648	
	School federation			
KPS*After-reform	0.033***	-	0.040***	-
	(0.007)		(0.006)	
District KPS*After-reform	-	0.026***	-	0.033***
		(0.009)		(0.007)
Municipal KPS*After-reform	-	0.050***	-	0.057***
		(0.010)		(0.007)
R^2	0.78	0.80	0.76	0.78
Obs (RC-years)	2,928		5,664	
	“pure” re-designation			
KPS*After-reform	0.034***	-	0.035***	-
	(0.008)		(0.006)	
District KPS*After-reform	-	0.025***	-	0.027***
		(0.009)		(0.007)
Municipal KPS*After-reform	-	0.056***	-	0.053***
		(0.010)		(0.007)
R^2	0.77	0.79	0.76	0.78
Obs (RC-years)	3.048		5,808	

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% respectively. Control variables include all regressors in Table 3, plus dummies for districts, and the full interaction between numbers of independent schools and the level of school.

Table 9 shows the MDID estimates for the pooled sample and by different channels, using both matching strategies. The MDID results are all statistically significant at the 1% level, regardless of level of the key school and the matching strategy chosen. Depending on the specific treatment, there is an around 4-6% and 2-3% increase in the price when an RC gains access to municipal and district KPS respectively. Consistent with the DID results in Table 7, school federation has the highest effect while multi-school dicing has the lowest effect on house prices, although the difference across treatment types might not be statistically significant. Moreover, the magnitudes are also larger than the standard DID results, which might be due to the failure of the critical common trend assumption for DID.

7. Robustness checks

In this section we undertake further robustness checks to ensure our findings are insensitive to the exclusion of all key primary schools from the control group, and to the number of independent schools in the surrounding areas. We will also investigate potential heterogeneous treatment effects with respect to the age and average number of floors of the residential complex, and to the distance to the CBD.[17]

7.1. Excluding all key primary schools from the control group

Recall that our control group includes all primary schools which have not experienced a status change over our sample period, regardless of their key school status at the beginning of the period. One might be concerned that while multi-school dicing and school federation reforms increase the attractiveness of the previously non-key schools, they might have an opposite effect on the pre-existing key schools involved, through perhaps a dilution of resources.[18] We deal with this issue by reanalysing the sample after excluding all key primary schools from the control group.

Compared to Table 6, we can see that the FE coefficients of the treatment variables in Table 10 remain statistically significant, and of the same magnitude. This suggests that our findings are not driven by the inclusion of pre-existing key primary schools in the control group. To the extent that the quality of the pre-existing key primary schools might deteriorate, the MDID estimates using a control group which include existing key primary schools could be too conservative.

[17] Table A2 in the Appendix present descriptive statistics by transition status over the sample period. The patterns indicate that the RCs which have experienced upgrading of the designated primary schools are unlikely to be randomly selected, as they tend to be closer to the CBD and the flats are smaller on average.

[18] Multi-school dicing reforms are normally implemented in such a way that **only** surplus places at the elite school concerned are allocated to nearby non-key school districts. This implies no one loses out and the enrolment lottery only applies to the latter group.

Table 10: Robustness checks with respect to the exclusion of pre-existing key primary schools, FE

	Full sample	Multi-school dicing	School federation	"Pure" re-designation
District KPS	0.00522	0.0465*	-0.0555***	-0.00116
	(0.00846)	(0.0273)	(0.0200)	(0.00844)
Municipal KPS	0.0455***	0.0407*	0.121***	0.0343*
	(0.0160)	(0.0222)	(0.0334)	(0.0180)
Observations (RC-years)	3,392	2,884	2,932	3,244
R^2	0.759	0.748	0.745	0.754

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% respectively. Control variables include all regressors in Table 3, plus dummies for districts, and the full interaction between numbers of independent schools and the level of school.

7.2. Age and average number of floors of the residential complex, and distance to the CBD

Table 11 checks the robustness of the MDID employing nearest neighbour within caliper, with respect to age and average number of floors of the residential complex, and distance to the CBD. Given that Figures 4 and 5 suggest both matching strategies appear to fit the data equally well, we prefer nearest neighbour matching which preserves a much larger proportion of the original sample. The first two columns compares RCs with years since construction below or above the median. The next two columns present the results by the average floors of districts. The last two columns present the results on the basis of distance to CBD.

Table 11 suggests that the elite school designation effect on house prices are more pronounced for RCs which are newer (i.e. with below median years since construction), closer to the city centre, and more densely populated (above median number of floors). However, as in Table 9, the effect of municipal KPS is always larger than that of district KPS, with the exception of RC with above median distance to the CBD, in which case both estimates are statistically insignificant.

Tables 12-14 repeat Table 11, but focus on the treatment effect of multi-school dicing, school federation, and pure "re-designation", respectively. The results turn out to be highly robust to that of Table 9, indicating no significant differences across the 3 channels.

Table 11: Robustness w.r.t. age and average number of floors of the residential complex and distance to the CBD, all RCs

	MDID					
	Years since construction		Distance to the CBD		Average number of floors	
	Below median	Above median	Below median	Above median	Below median	Above median
District KPS	0.0105	0.00434	0.0602***	-0.00777	-0.0200	0.0437***
	(0.0133)	(0.0138)	(0.0126)	(0.0146)	(0.0129)	(0.0141)
Municipal KPS	0.134***	0.101***	0.149***	0.138***	0.114***	0.150***
	(0.0182)	(0.0246)	(0.0177)	(0.0221)	(0.0184)	(0.0212)
District KPS * After-reform	0.0283***	0.0205**	0.0389***	0.00621	0.0254**	0.0274***
	(0.00867)	(0.0101)	(0.0111)	(0.0142)	(0.0110)	(0.00880)
Municipal KPS * After-reform	0.0592***	0.0335***	0.0915***	-0.000209	0.0352***	0.0582***
	(0.00852)	(0.0127)	(0.0129)	(0.0150)	(0.0102)	(0.0123)
Obs (RC-years)	2,744	3,224	1,492	1,492	2,984	2,984
R^2	0.802	0.686	0.750	0.727	0.788	0.664

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% respectively. The observations are matched based on the Nearest Neighbourhood Matching. MDID estimates by subgroups. Control variables as in Table 5.

Table 12: Robustness w.r.t. age and average number of floors of the residential complex and distance to the CBD, Multi-school Dicing

	MDID					
	Years since construction		Distance to the CBD		Average number of floors	
VARIABLES	Below median	Above median	Below median	Above median	Below median	Above median
District KPS	0.0200	0.000942	0.0598***	-0.0153	-0.0152	0.0381***
	(0.0139)	(0.0140)	(0.0125)	(0.0151)	(0.0138)	(0.0145)
Municipal KPS	0.143***	0.0990***	0.145***	0.132***	0.126***	0.146***
	(0.0188)	(0.0255)	(0.0180)	(0.0222)	(0.0190)	(0.0228)
District KPS*After-reform	0.0337***	0.0278***	0.0488***	0.0135	0.0257**	0.0367***
	(0.00836)	(0.00994)	(0.0102)	(0.0128)	(0.0112)	(0.00855)
Municipal KPS*After-reform	0.0648***	0.0333***	0.101***	0.0122	0.0398***	0.0631***
	(0.00828)	(0.0128)	(0.0119)	(0.0145)	(0.0103)	(0.0124)
Obs (RC-years)	2,536	3,112	1,412	1,412	2,824	2,824
R^2	0.808	0.680	0.758	0.725	0.792	0.655

Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10% respectively. The observations are matched based on the Nearest Neighbourhood Matching. MDID estimates by subgroups. Control variables as in Table 5.

Table 13: Robustness w.r.t. age and average number of floors of the residential complex and distance to the CBD, School Federation

	MDID					
	Years since construction		Distance to the CBD		Average number of floors	
	Below median	Above median	Below median	Above median	Below median	Above median
District KPS	0.0152	0.00672	0.0529^{***}	-0.0133	-0.0128	0.0459^{***}
	(0.0139)	(0.0142)	(0.0126)	(0.0151)	(0.0135)	(0.0144)
Municipal KPS	0.139^{***}	0.113^{***}	0.138^{***}	0.134^{***}	0.133^{***}	0.154^{***}
	(0.0186)	(0.0256)	(0.0177)	(0.0223)	(0.0188)	(0.0221)
District KPS * After-reform	0.0396^{***}	0.0260^{***}	0.0496^{***}	0.0223^{*}	0.0249^{**}	0.0392^{***}
	(0.00894)	(0.0100)	(0.0105)	(0.0129)	(0.0109)	(0.00889)
Municipal KPS * After-reform	0.0687^{***}	0.0397^{***}	0.113^{***}	0.0243^{*}	0.0453^{***}	0.0647^{***}
	(0.00824)	(0.0132)	(0.0121)	(0.0145)	(0.0101)	(0.0123)
Obs (RC-years)	2,608	3,056	1,416	1,416	2,832	2,832
R^2	0.804	0.678	0.766	0.722	0.796	0.655

Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10% respectively. The observations are matched based on the Nearest Neighbourhood Matching. MDID estimates by subgroups. Control variables as in Table 5.

Table 14: Robustness w.r.t. age and average number of floors of the residential complex and distance to the CBD, "Pure" Re-designation

	MDID					
	Years since construction		Distance to the CBD		Average number of floors	
VARIABLES	Below median	Above median	Below median	Above median	Below median	Above median
District KPS	0.0176	0.00415	0.0621^{***}	-0.00639	-0.0104	0.0373^{***}
	(0.0132)	(0.0139)	(0.0122)	(0.0149)	(0.0131)	(0.0141)
Municipal KPS	0.133^{***}	0.101^{***}	0.139^{***}	0.133^{***}	0.117^{***}	0.145^{***}
	(0.0184)	(0.0258)	(0.0177)	(0.0232)	(0.0187)	(0.0227)
District KPS * After-reform	0.0235^{***}	0.0253^{**}	0.0336^{***}	0.00914	0.0153	0.0350^{***}
	(0.00833)	(0.0101)	(0.0107)	(0.0142)	(0.0109)	(0.00882)
Municipal KPS * After-reform	0.0615^{***}	0.0396^{***}	0.0967^{***}	0.00970	0.0402^{***}	0.0628^{***}
	(0.00861)	(0.0128)	(0.0122)	(0.0155)	(0.0106)	(0.0123)
Obs (RC-years)	2,684	3,124	1,452	1,452	2,904	2,904
R^2	0.802	0.678	0.759	0.717	0.788	0.652

Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10% respectively. The observations are matched based on the Nearest Neighbourhood Matching. MDID estimates by subgroups. Control variables as in Table 5.

7.3. Robustness check based on the new classification.

We are aware that the estimated effects could be biased if the historical key school status becomes obsolete. Hence, we present results based on a different school classification. The alternative prestige ranking is based on the unofficial league tables from a popular parenting support website.[19] The three different prestige tiers have been converted to first, second and third class respectively. Table A3 cross tabulates the two classifications, which suggests a very high correlation indeed. Note that a few ordinary primary schools classified on the basis of the objective historical ranking are now reclassified as first class under the subjective but more up-to-date

[19] www.jzb.com/bbs/bj.

parental rating. This is consistent with the small number of ordinary schools with superb achievements in terms of academic tournament awards in Table 1. If anything, including these high-performing in the control group in the main analysis would make our estimates more conservative, in the sense of making it less likely to find significant impacts of quality schools on housing prices.

Table 15 presents the MDID results using the Nearest Neighbour strategy based on the new classification, using the sample of residential complexes with non-missing parental subjective ranking. Consistent with Table 9, it clearly shows that the house prices of residential complex which gain access to a first-class school increase significantly by about 4%, while the price premiums for both second and third class schools are about 3%. These findings lend further support to our main results based on the objective historical school classification.

Table 15: Matching Differences-in-differences estimates, alternative school classification

VARIABLES	(1) All	(2) Multi-school dicing	(3) School federation	(4) "Pure" re-designation
First class	0.248***	0.245***	0.252***	0.262***
	(0.0301)	(0.0310)	(0.0303)	(0.0297)
Second class	0.187***	0.185***	0.186***	0.182***
	(0.0192)	(0.0201)	(0.0200)	(0.0199)
Third class	0.0302**	0.0393***	0.0485***	0.0326**
	(0.0138)	(0.0139)	(0.0143)	(0.0139)
Time	0.283***	0.292***	0.277***	0.280***
	(0.00654)	(0.00712)	(0.00794)	(0.00662)
First class*After-reform	0.0491**	0.0337	0.0465**	0.0463**
	(0.0239)	(0.0231)	(0.0233)	(0.0229)
Second class*After-reform	0.0334**	0.0250*	0.0364**	0.0376***
	(0.0143)	(0.0144)	(0.0145)	(0.0138)
Third class*After-reform	0.0292***	0.0153	0.0376***	0.0335***
	(0.00911)	(0.00951)	(0.0101)	(0.00911)
Obs (RC-years)	1,760	1,416	1,480	1,724
R^2	0.645	0.661	0.632	0.640

Notes: The sample consists of a two-wave panel from year 2013 and 2016, and drops residential complexes which don't have the subjective classification. The results are based on the nearest neighbour strategy, which preserves more observations compared to the Mahalanobis distance matching, it includes more observations.. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

8. Concluding Remarks

This paper examines the effect of recent comprehensive educational reforms which aim to equalize access to elite elementary schools on house prices in Beijing, China. While the *multi-school dicing* reform involves randomly assigning previously ineligible pupils to key elementary schools through lotteries by enlarging the effective school attendance zone, the reform of *school federation* *led by elite schools* consolidates low quality schools through alliance with elite schools. Moreover, an RC can experience a *"pure" re-designation* effect, if the designated school change from an ordinary primary school to a key primary school.

Using the Matching Difference-in-Differences (MDID) approach to address potential endogenous treatment, we identify the effect of gaining access to an elite primary schools on house prices while allowing for underlying systemic differences between the treated and non-treated school districts. Our estimates suggest that the price premium of being eligible to enrol in a municipal-level key primary school is about 4-6%, while the premium for being eligible for a district-level key primary school is about 2-3%, with both effects very precisely determined. The three different channels have similar effects but with slightly different magnitudes. School districts which have undertaken school federation reforms are likely to experience slightly higher increase in prices. The magnitude of these results is in line with the limited causal evidence on the price premium of quality school access in China currently available.

Our findings are robust to the use of alternative matching strategies. We also find that excluding all pre-existing key primary schools from the control group, makes little difference to our conclusions, as far as the fixed-effect estimates are concerned. To the extent that multi-school dicing and school federation might lead to dilution of resources of the existing key primary schools, our estimates should be interpreted as a lower bound effect. Moreover, the elite school designation effect on house prices are found to be more pronounced for residential complexes which are newer, more densely populated and closer to the city centre, holding all other factors constant. Our findings are also robust to an alternative measure of primary school prestige based on an up-to-date unofficial ranking from a popular parenting support website, which is shown to be closely related to the number of awards in academic tournaments by the schools.

One limitation of our study is that we do not have measures of the probability of enrolment into a key school under multi-school dicing or the exact formation of the school federation led by an elite school. Having "proxies" for such variation would have allowed us to discriminate between treatments of various intensity. While we present suggestive evidence that the choice of different treatment mechanisms might reflect preferences of the local education authorities of different districts, uncovering the underlying causes is certainly beyond the scope of the current study, in the absence of better data.

Nevertheless, our findings have important policy implications. Although both the multi-school dicing and the school federation reforms aim to equalize education opportunities for all pupils in Beijing, they are shown to have the unintended consequences of pushing up house prices that are already out of reach for people on average earnings in this metropolis. Future educational policy reforms would benefit from careful evaluations of similar programmes implemented in different contexts and possibly randomized controlled pilot studies.

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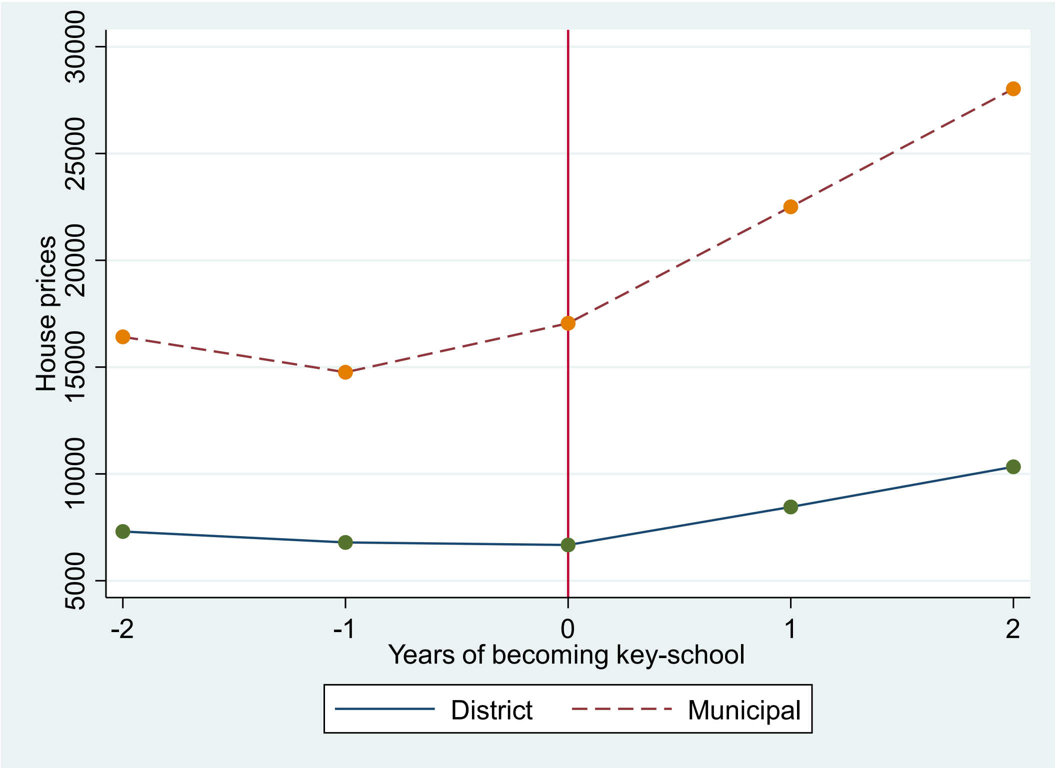
Appendix:

Figure A1: Trend of real house prices by treatment type, with ordinary schools in the control group only



Notes: The vertical axis show the real price premiums of the treated group by key school level, relative to the control group of all RCs affiliated with ordinary schools only over time. Compared to Figure 2, the control group now excludes all RCs affiliated with pre-existing key schools.

Table A1: Impacts of pre-determined characteristics on treatment type

VARIABLES	(1) Full Sample	(2) Multi-school dicing	(3) School federation	(4) Pure re-designation
Greening rate	0.332	0.900	0.835	-1.111
	(0.485)	(1.516)	(1.253)	(0.894)
Mean floor area ratio	0.00151	0.0546	-0.0334	0.0443
	(0.0205)	(0.0474)	(0.0705)	(0.0290)
Service charges	-0.0353	-0.0179	0.0150	-0.100*
	(0.0342)	(0.113)	(0.0864)	(0.0606)
Mean floor area per flat	0.00130	-0.00377	-0.00366	0.000460
	(0.00123)	(0.00441)	(0.00399)	(0.00217)
# floors	-0.00508	-0.00499	-0.0149	-0.00423
	(0.00564)	(0.0187)	(0.0158)	(0.0102)
Distance to City Centre	0.0136**	-0.0161	-0.0208	0.0295**
	(0.00664)	(0.0259)	(0.0283)	(0.0147)
Dist. to nearest top-grade hospital	-0.0765***	0.114*	-0.0525	-0.0969**
	(0.0223)	(0.0676)	(0.0839)	(0.0432)
Dist. to nearest subway station	-0.293***	0.495	0.569	-0.265*
	(0.0626)	(0.444)	(0.821)	(0.141)
Dist. to nearest subway station sq.	0.0182***	-0.124	-0.323	0.0112
	(0.00649)	(0.122)	(0.437)	(0.00945)
Chaoyang District	0.135	0.0922	0.706***	0.351*
	(0.139)	(0.445)	(0.265)	(0.208)
Haidian District	0.667***	-0.0818	-	-0.153
	(0.153)	(0.493)		(0.238)
Xicheng District	0.624***	-0.0878	0.833**	-0.972**
	(0.166)	(0.531)	(0.333)	(0.408)
Other districts	-0.669***	-0.271	-	-0.958***
	(0.149)	(0.497)		(0.286)
Constant	0.174	-2.758***	-2.155***	-0.974***
	(0.197)	(0.665)	(0.665)	(0.326)
Observations	1,907	1,783	1,437	1,864

Notes: The sample of the results includes RCs in 2013, i.e. before treatment taking place. The results are based on Probit model and time-invariant characteristics of RCs.

Table A2: Descriptive statistics, by status change

Status 2013-2016	Distance to city centre (km)	Mean floor area (m^2)	Year of construction
Ordinary in both years	13.70	86.56	2001
District-level KPS in both years	11.55	87.17	2001
Municipal-level KPS in both years	9.28	83.03	1997
Ordinary to District-level KPS	10.25	82.96	1997
Ordinary to municipal-level KPS	8.44	74.24	1996
Total	12.82	85.84	2000

Table A3: Relationship between the two school classifications

2013	Municipal KPS	District KPS	Ordinary	Total
First class	21	0	8	29
Second class	37	8	4	49
Third class	7	14	9	30
Others	151	319	460	930
Total	216	341	481	1,038

2016	Municipal KPS	District KPS	Ordinary	Total
First class	45	0	0	45
Second class	63	15	6	84
Third class	88	49	2	139
Others	53	88	356	119
Total	249	273	364	1,038

Notes: The alternative prestige ranking is based on the unofficial league tables from the popular parenting support website www.jzb.com/bbs/bj. The three different tiers have been converted to first, second and third class respectively. The sample drops residential complexes which don't have the alternative ranking, first class; second class; third class.