Elite School Designation and Housing Prices -

Quasi-experimental Evidence from Beijing, China

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Abstract

We explore recent policy changes which aim to equalize access to elite elementary schools in Beijing in order 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 is linked to 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 alliances 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 4-8%, 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 two alternative measures of primary school prestige: an unofficial ranking from a popular parenting support website; and the number of awards in academic tournaments.

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 between and within regions. The so-called system of "key schools and universities" dated 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). While both types of schools are publicly funded, a key primary school (KPS) is perceived to offer substantially better education quality compared to an ordinary primary school (OPS) due to higher per capita funding, better teacher quality, and highly favourable student socio-economic backgrounds (You 2006). However, the detrimental effect of key schools on education equity has become an increasing concern for the policymakers and the public. Following the introduction of 9-year compulsory education, the authorities formally prohibited *key schools* from the compulsory education stage in the 1990s. Nevertheless, parents still seem to highly value those traditional elite schools, even without the official labelling. In response to parental demand for access to quality schools, the educational authorities in Beijing have attempted to extend the coverage of KPSs. Between 2013 and 2016, the proportion of students attending a KPS in Beijing in increased from 39.6% to 46.5%, or 17% in relative terms.

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 such as 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 which give 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, 2013 house prices in Beijing's elite school districts were on average roughly 30 percent higher than in other districts (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 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 features of properties, as well as neighbourhood and location characteristics, the mean house price in key primary school catchment areas is about 6% higher than that of ordinary primary school catchment areas in the Ordinary Least Squares specification.

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 5-8%, 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.

Our paper is similar to Feng and Lu (2013), the only causal study of the effect of school quality on house prices in China published in English to date. Using a DID approach, they find that the re-designation of the status of an ordinary high school to a specific high-quality school status increases the house price in its residential area by 6.9% in Shanghai. Compared to their study, our paper also addresses the potential endogeneity bias arising from the non-random school designation policies through a matching DID strategy. We also undertake extensive robustness analysis using two different tiers of KPSs and three alternative classifications of key primary schools. Furthermore, we explore three different channels through which the school re-designation may affect housing prices in the relevant residential complexes.

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 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 on average by about 15% per annum between 2002 and 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 education resources, particularly in higher education. However, competition for entry into the elite schools which have a proven record of enrolling students into the country's best known universities, is fierce and starts well before the formal entry into 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 city districts 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 acted as models for pupils and teachers in local ordinary

[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.

schools and sometimes as showcases of New China's educational achievement to 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. This proportion increased by almost 7 percentage points (or 17%) to 46.5% in 2016.

With the aim of equalizing access to elite schools, 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 based on their history. 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, our sensitivity analysis tests the robustness of our result using two alternative school classifications: one obtained from a popular parenting support website which collects subjective rankings of parents regarding the performance of schools;[3] and another from the number of prestigious academic awards. While these are not official rankings, they show strong consistency and very high correlation with the objective historical quality measures.

Although we are unable to provide direct measures of academic success by types of schools, we can show that the classification of school types we use are closely related to the number of awards received in the prestigious municipal-level academic tournaments over the sample period.[4] The medals are designed to honour students for outstanding achievements in exams, sports, art activities, and national or international science competitions by the municipal government of Beijing.[5] A higher number of medals indicates a school's better education quality and serves as a strong signal to parents when choosing a school.

Table 1 describes the number of awards gained before 2013 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

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

[4] Chan et al. (2018) also uses tournament performance as a quality indicator in their study of primary school quality on housing market 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.

many academic tournament awards reflects the fact that the school classification is based on pre-2000 records. In the sensitivity analysis we explore a subjective but more up-to-date classification which treat high-performing ordinary schools as elite.

Table 1: Number of awards in municipal-level academic tournaments by school type

	0	**1-2**	**3-4**	**5+**	**Total**
Ordinary Primary School	1,202	10	7	9	1,228
District KPS	416	20	17	0	453
Municipal KPS	141	23	23	38	226
Total	1,759	54	47	47	1,907

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

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 education inequality, the district governments have discretion in the way that the policy is implemented. Importantly, we expect school re-designation to be an 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 given 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.

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

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 what we label a ***"pure" re-designation***, if the designated school is changed from an ordinary school to a key primary school. Note that under ***"pure" re-designation***, students in a RC are simply assigned to a new school which is labelled as being higher quality, without any change in the actual quality of the school involved.

Conceptually, these policies can be regarded as representing the three different approaches to improving 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 giving parents the opportunity to access an elite school, albeit with a low probability. 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 viewed as an improvement that works through the administrative mechanism. 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 important for both policymakers and the public 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 design, 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, to 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 housing 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, they argue that the introduction of an inter-district choice program drove relatively high-income households 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 schools inside and outside the district. After the school choice reform, the residential prices in previously high performing school districts fell by around 10-27% relative to low-performing districts. Machin and Salvanes (2016) evaluate the effects of altering the policy from enrolment to the nearest school to an open enrolment policy 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 near 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 controversial school performance tables, sometimes known as league tables. Empirical studies have suggested that information on a 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 students achieve better academic performance compared to randomly picked schools from the choice set. Burgess et al. (2015) show that the majority of households in the UK have a strong preference for

[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.

schools with good academic performances.[8] Based on a boundary discontinuity design, Harjunen et al. (2018) demonstrate that a one standard deviation increase in average test scores pushed up relevant house prices by 2.5% in Helsinki.

To the best of our knowledge, only a 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 the status of an ordinary high school to a specific high-quality school status increases the house price in its residential area by 6.9% in Shanghai. However, as the school designation policy implemented by the municipal government is not entirely exogenous, e.g. due to concerns for equal access across geographical areas, endogeneity bias may be present in the DID estimates.

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, 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, the canonical DID estimator would suffice to uncover the true causal effect with the help of a well-defined control group which

[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.

is assumed to share the common trend prior to treatment. Our case is complicated by the fact that the school re-designation might take place at any time between 2013 and 2016, which may result in ambiguous results (Goodman-Bacon 2018). Given that the DID design with time varying treatment is still at the frontier of econometrics, we have chosen to simplify the empirical design and employ a canonical DID with two time periods, one before and one after the treatment. Therefore, the analytical sample consists of a two-period balanced panel data consisting of year 2013 and year 2016.

Following the literature, we choose the semi-log specification:

$$lnprice_{it} = \beta_0 + \beta_1 Keysch_{it} + \delta X_{it} + \varepsilon_{it} \quad (1)$$

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

where $lnprice_{it}$ is the logarithm of mean house price of residential complex i in year t, $Keysch_{it}$ 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), X_{it} is a vector of control variables, ε_{it} is the error term, and β_0, β_1, and δ 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:

$$Y_{it} = \alpha_1 + \alpha_2 after_t + \alpha_3 Keysch_{it} + \alpha_4 after_t * Keysch_{it} + \alpha_5 X_{it} + \varepsilon_{it} \quad (2)$$

where $after_t$ equals one if the calendar year is 2016. The interaction 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:

$$E\left(Y_{0,t} - Y_{0,t'} \middle| X_{it}, Keysch_{it} = 0\right) = E(Y_{0,t} - Y_{0,t'} | X_{it}, Keysch_{it} = 1) \quad (3)$$

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 ordinary schools in certain areas led by existing elite schools to improve the access to elite education geographically.[9] In other words, the *non-ignorable treatment*

[9] 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,

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 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, service charges, level of facilities, distance to hospital, distance to city centre, and distance to business centre. The characteristics are time-invariant and historical information. Given the assumption of "Strong Ignorability" proposed by Rosenbaum and Robin (1985), $0<P(Keysch_{it}=1|X)<1$. Together with the previous two equations, this 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) $$E\left(Y_{0,t} - Y_{0,t'} \middle| P(Z), Keysch_{it} = 0\right) = E(Y_{0,t} - Y_{0,t'} | P(Z), Keysch_{it} = 1)$$

4.1 Channels

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.[10] In reality, people may doubt how much resources would be redistributed from the leading elite school to the low-

they do not account for the non-random assignment of the reformed schools.

[10] 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).

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 of Beijing over the period 2013-2016.[11] 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-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/).[12] 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

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

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

relevant school status and any regime changes during the sample period, using school admissions booklets or the websites of the district education authorities.[13]

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. We have also dropped one RC whose designated primary school was downgraded from KPS to ordinary primary school. The final sample is a balanced panel of 1,907 RCs, each observed in both 2013 and 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] 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 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 changed 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.[14]

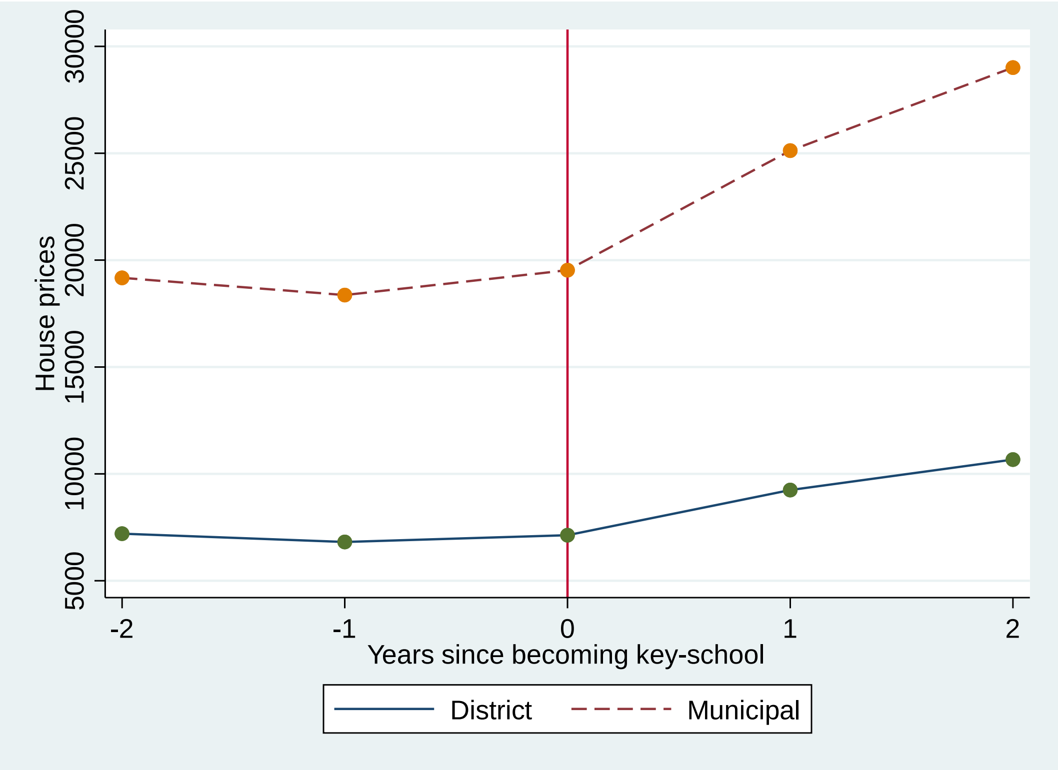
Figure 3 shows the corresponding time trend, by treatment type. Because of small cell sizes, the graph only shows mean real housing prices from the year immediately before the school status change. Again, all 3 treatment types have the same pre-treatment time trend, relative to the omitted control group 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

[14] 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 a higher chance of re-designating RCs to better schools.

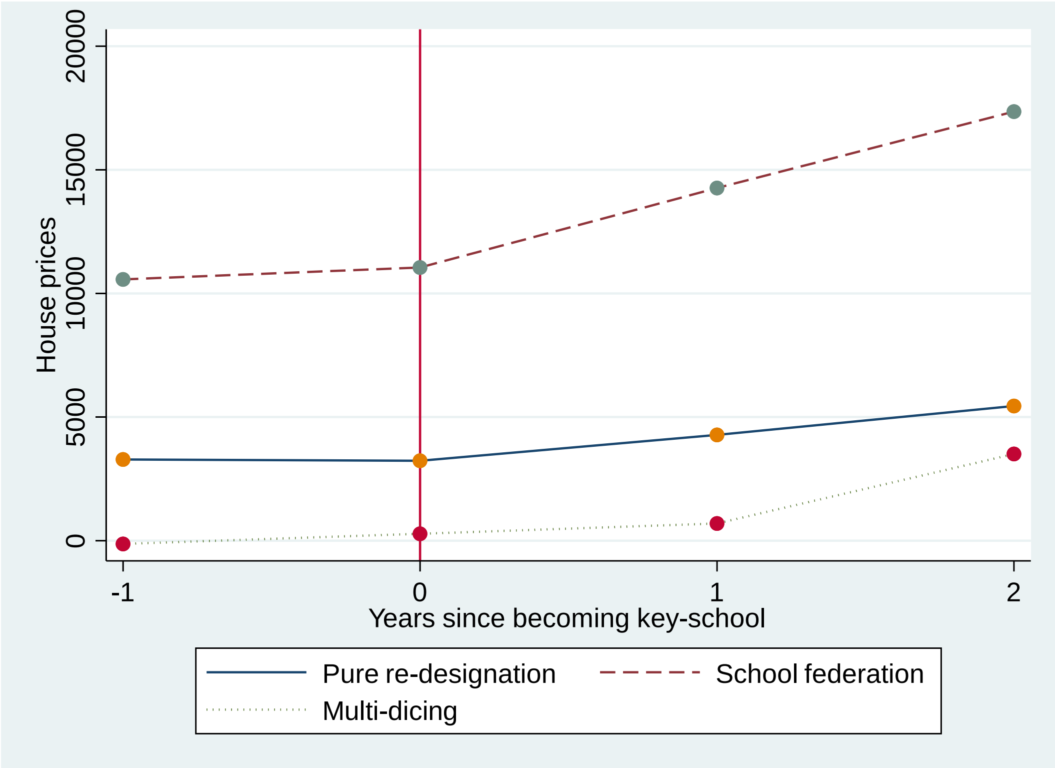
Table A1 in the Appendix shows the results of running a treatment dummy on baseline (2013) RC characteristics for the full sample, and by treatment type. It turns out that that none of the RC characteristics are significant determinants of the treatment status or type. On the other hand, the distance 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.

Figures A2 and A3 in the Appendix show the corresponding conditional time trend plots, i.e. residuals of real house prices from the hedonic regressions. The patterns are fully consistent with the time trends in unconditional house prices in Figures 2 and 3.

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 37,707 RMB yuan (USD 5976) in 2013, to 50,657 yuan (USD 8028) in 2016, an increase of 34.3% in real terms over 3 years.[15] Over the same period, 6.9% of RCs experienced a change in the status of the designated primary school. While in 2013 39.6% of all residential complexes are in the school district (SD) of a Key primary school, two thirds of which are district-level KPSs, the share of elite SDs grows to 46.0% in 2016.

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) per month per square metre. The mean number of floors is 12.3, reflecting the fact that Beijing is a very densely populated metropolis. The mean floor area per flat is 85.8m^2, while the average year of construction is 2000. The straight-line distances to the city centre and the nearest top-grade hospital are 12.3 and 2.4 km respectively, while the distance

[15] We use the mean year-end exchange rate of 6.31 CNY per USD over the 2013-2016 period for conversion.

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. Dongcheng and the Xicheng District are the centre of the city and also have more key schools compared to other parts of the city. Over the sample period, there is a significant increase in the coverage of key schools, especially for district key schools.

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 the corresponding DID estimates, with and without 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.[16]

[16] We focus on the canonical two-period DID results in the main text. While in practice, the treatment can take place at different years during the sample period, the most recent econometrics literature has shown that the canonical two-period DID is a weighted average of all possible 2X2 DIDs allowing for time-varying treatments (see Athey and Imbens (2018) and Bacon (2018)). Appendix B demonstrates that our canonical DID estimates can be decomposed into the various components, following the Stata routine "*bacondecomp*" developed by Goodman-Bacon et al. 2019.

Table 5: Effect of school designation on house prices, OLS and DID

	OLS		DID	
	(1)	(2)	(3)	(4)
KPS	0.0653***		0.0513***	
	(0.00744)		(0.00790)	
After-reform	0.230***	0.230***	0.205***	0.203***
	(0.00672)	(0.00668)	(0.00807)	(0.00807)
KPS*After-reform			0.0385***	
			(0.00712)	
District KPS (DKPS)		0.0362***		0.0239***
		(0.00799)		(0.00823)
Municipal KPS (MKPS)		0.149***		0.114***
		(0.0123)		(0.0129)
DKPS *After-reform				0.0258***
				(0.00798)
MKPS *After-reform				0.0685***
				(0.00966)
# Independent schools (within 10km)	0.0147***	0.0142***	0.0146***	0.0142***
	(0.00155)	(0.00153)	(0.00155)	(0.00153)
Greening rate	0.194***	0.202***	0.194***	0.202***
	(0.0611)	(0.0597)	(0.0612)	(0.0597)
Mean floor area ratio	-0.0092***	-0.0089***	-0.0093***	-0.009***
	(0.00278)	(0.00260)	(0.00279)	(0.00260)
Service charges	0.0340***	0.0342***	0.0341***	0.0343***
	(0.00583)	(0.00591)	(0.00583)	(0.00591)
Mean floor area per flat	-0.0007***	-0.0007***	-0.0007***	-0.0007***
	(0.000190)	(0.000189)	(0.000190)	(0.000189)
# Floors	-0.0021***	-0.0018**	-0.0007***	-0.0007***
	(0.000742)	(0.000732)	(0.000190)	(0.000189)
# Local amenities	0.103***	0.108***	-0.0021***	-0.0018**
	(0.0134)	(0.0193)	(0.000742)	(0.000731)
Distance to City Centre	0.00648***	0.00660***	-0.0198***	-0.0197***
	(0.000574)	(0.000575)	(0.000689)	(0.000676)
Distance to City Centre*After-reform	-0.0226***	-0.0230***	0.00672***	0.00707***
	(0.00286)	(0.00283)	(0.000574)	(0.000579)
Dist. to nearest top-grade hospital	0.000164	-0.000303	-0.0231***	-0.0236***
	(0.00197)	(0.00200)	(0.00286)	(0.00283)
Dist. to nearest top-grade hospital*After-reform	-0.0212***	-0.0218***	0.00123	0.000809
	(0.00582)	(0.00579)	(0.00199)	(0.00202)
Dist. to nearest subway station	-0.0218***	-0.0219***	-0.0226***	-0.0228***
	(0.00518)	(0.00518)	(0.00582)	(0.00579)
Dist. to nearest subway station*After-reform	0.00004***	0.00004***	-0.0188***	-0.0197***
	(0.000469)	(0.000451)	(0.00517)	(0.00514)
Dist. to nearest subway station sq.	0.00007	0.00008	0.00403***	0.00407***
	(0.000314)	(0.000312)	(0.000470)	(0.000454)
Dist. to nearest subway station sq. *After-reform	0.00648***	0.00660***	-0.000177	-0.000123
	(0.000574)	(0.000575)	(0.000321)	(0.000322)
Chaoyang District	-0.157***	-0.134***	-0.158***	-0.134***
	(0.0168)	(0.0168)	(0.0168)	(0.0168)
Haidian District	0.0828***	0.0805***	0.0831***	0.0815***
	(0.0186)	(0.0179)	(0.0186)	(0.0179)
Xicheng District	0.127***	0.127***	0.127***	0.127***
	(0.0205)	(0.0197)	(0.0205)	(0.0196)
Other districts	-0.270***	-0.250***	-0.270***	-0.249***
	(0.0175)	(0.0175)	(0.0175)	(0.0175)
Observations (RC-years)	3,814	3,814	3,814	3,814
R^2	0.803	0.810	0.803	0.811

Note: Standard errors clustered at RC level. ***, ** 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.

Column 1 shows that the regression adjusted price premium of access to a key primary school is 6.5%. 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 that of its district-level counterpart, at 14.9% and 3.6% respectively, both statistically significant at the 1% level. Columns 3 and 4 present the corresponding DID estimates. This time the re-designation as an elite school increases house prices by 2.6% and 6.9% for district and municipal KPS respectively, both statistically significant at the 1% level. Note that the estimated time effect for the post-treatment period is remarkably consistent across all specifications, within the range of 0.203-0.230. These correspond to an increase in real house prices of approximately 22.5% - 25.9% over three years.

Table 6 presents DID results in treatment type with similar setting as for Table 5. The magnitudes of DID estimates for municipal key primary schools are marginally smaller, at around 7-8% 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 at less than 3%.

Table 6: DID by type of treatment

	Multi-school dicing		School federation		"Pure" re-designation	
	(1)	(2)	(3)	(4)	(5)	(6)
KPS	0.0716^{***}		0.0542^{***}		0.0542^{***}	
	(0.00851)		(0.00832)		(0.00811)	
After	0.205^{***}	0.203^{***}	0.204^{***}	0.201^{***}	0.201^{***}	0.199^{***}
	(0.00790)	(0.00794)	(0.00786)	(0.00789)	(0.00807)	(0.00807)
KPS*After-reform	0.0393^{***}		0.0428^{***}		0.0377^{***}	
	(0.00694)		(0.00703)		(0.00723)	
District KPS		0.0341^{***}		0.0312^{***}		0.0307^{***}
		(0.00872)		(0.00868)		(0.00856)
Municipal KPS		0.130^{***}		0.127^{***}		0.126^{***}
		(0.0141)		(0.0141)		(0.0137)
District KPS*After-reform		0.0264^{***}		0.0268^{***}		0.0259^{***}
		(0.00777)		(0.00782)		(0.00810)
Municipal KPS*After-reform		0.0686^{***}		0.0773^{***}		0.0683^{***}
		(0.00997)		(0.0101)		(0.0100)
Observations (RC-years)	3,432	3,432	3,458	3,458	3,594	3,594
R^2	0.797	0.812	0.804	0.812	0.801	0.809

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 7 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 results after matching show that the matching has been successful, for both strategies.

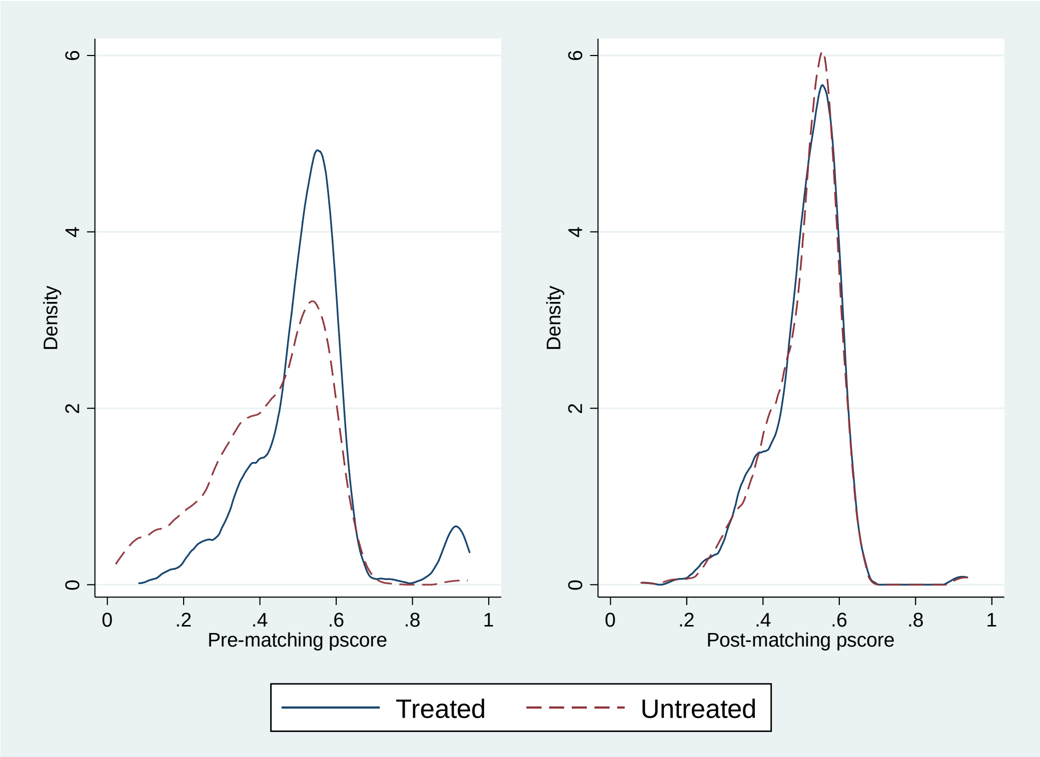
Table 7: Post-matching balancing tests

	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	

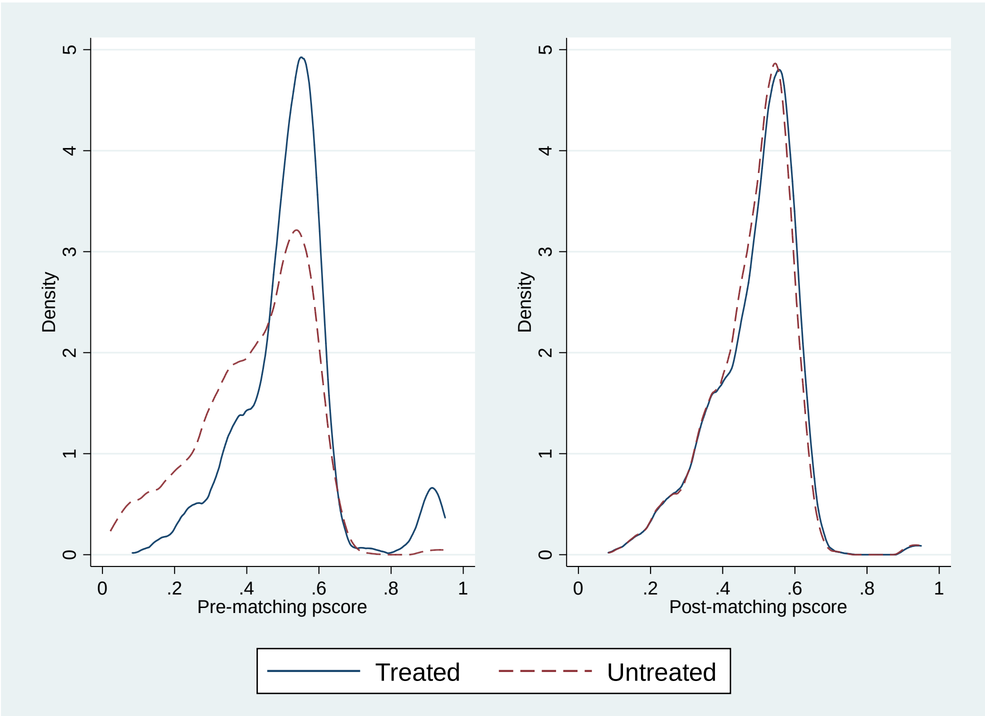
Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% respectively.

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

	Mahalanobis		Nearest Neighbour	
	All			
KPS*After-reform	0.030**	-	0.037***	-
	(0.01)		(0.01)	
District KPS*After-reform		0.023*		0.027**
		(0.01)		(0.01)
Municipal KPS*After-reform	-	0.045***	-	0.063***
		(0.01)		(0.01)
R^2	0.78	0.79	0.78	0.78
Obs (RC-years)	1,580		2,984	
	Multi-school dicing			
KPS*After-reform	0.031**	-	0.042***	-
	(0.01)		(0.01)	
District KPS*After-reform	-	0.025*	-	0.029***
		(0.01)		(0.01)
Municipal KPS*After-reform	-	0.044***	-	0.069***
		(0.01)		(0.01)
R^2	0.78	0.79	0.78	0.78
Obs (RC-years)	1,472		2,824	
	School federation			
KPS*After-reform	0.038***	-	0.049***	-
	(0.01)		(0.01)	
District KPS*After-reform	-	0.024*	-	0.034***
		(0.01)		(0.01)
Municipal KPS*After-reform	-	0.067***	-	0.080***
		(0.01)		(0.01)
R^2	0.78	0.80	0.76	0.78
Obs (RC-years)	1,464		2,832	
	"Pure" re-designation			
KPS*After-reform	0.027**	-	0.038***	-
	(0.01)		(0.01)	
District KPS*After-reform	-	0.016	-	0.026**
		(0.01)		(0.01)
Municipal KPS*After-reform	-	0.055***	-	0.070***
		(0.01)		(0.01)
R^2	0.77	0.79	0.76	0.78
Obs (RC-years)	1,524		2,904	

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

Table 8 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 approximately 4-8% and 2-3% increase in the price when a RC gains access to a municipal and district KPS, respectively. Consistent with the DID results in Table 6, school federation has the highest effect while multi-school dicing has the lowest effect on house prices, although the difference across treatment types may 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 in Table 9 the DID coefficients of the treatment effects for municipal KPSs have become more pronounced while those for district KPSs have become statistically insignificant. 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 that includes existing key primary schools could be too conservative, especially for municipal KPS.

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[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 9: Robustness of DID w.r.t. the exclusion of pre-existing key primary schools

	All (1)	Multi-school dicing (2)	School federation (3)	"Pure" re-designation (4)
District KPS (DKPS)	0.0467***	0.0307	0.105***	0.0349*
	(0.0177)	(0.0520)	(0.0334)	(0.0205)
Municipal KPS (MKPS)	0.0628***	0.0400	0.135***	0.0421
	(0.0217)	(0.0304)	(0.0394)	(0.0308)
After-reform	0.181***	0.174***	0.176***	0.175***
	(0.0100)	(0.0101)	(0.0101)	(0.00998)
District KPS (DKPS)# After-reform	0.00594	0.0942	-0.0411*	0.0113
	(0.0130)	(0.0599)	(0.0233)	(0.0142)
Municipal KPS (MKPS)# After-reform	0.122***	0.0687*	0.210***	0.0848***
	(0.0259)	(0.0408)	(0.0475)	(0.0327)
Observations	2,302	2,044	2,070	2,200
R-squared	0.802	0.794	0.800	0.795

Notes: The sample excludes the pre-existing key primary schools. ***, ** 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 10 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 number of floors of buildings in districts. The last two columns present the results based on distance to the CBD.

Panel A using all RCs 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 8, the effect of municipal KPSs is always larger than that of district KPSs, with the exception of RCs with above median distance to the CBD, in which case both estimates are statistically insignificant.

Panels B through D repeat Panel A, 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 8, indicating no significant differences across the 3 channels.

Table 10: Robustness of MDID w.r.t. age and average number of floors of the residential complex and distance to the CBD

	Years since construction		Distance to the CBD		Average number of floors	
	Below median	**Above median**	**Below median**	**Above median**	**Below median**	**Above median**
			Panel A: all RCs			
District KPS * After-reform	0.0392^{***}	0.0155	0.0370^{***}	0.00337	0.0347^{**}	0.0249^{**}
	(0.0119)	(0.0114)	(0.0114)	(0.0140)	(0.0135)	(0.0113)
Municipal KPS * After-reform	0.0758^{***}	0.0464^{**}	0.0878^{***}	-0.00000	0.0505^{***}	0.0821^{***}
	(0.0117)	(0.0190)	(0.0133)	(0.0149)	(0.0147)	(0.0176)
Obs (RC-years)	1,372	1,612	1,492	1,492	1,491	1,493
R^2	0.815	0.691	0.750	0.727	0.797	0.681
			Panel B: Multi-school Dicing			
District KPS*After-reform	0.0370^{***}	0.0220^{**}	0.0462^{***}	0.0101	0.0236^{*}	0.0377^{***}
	(0.0106)	(0.0111)	(0.0106)	(0.0124)	(0.0129)	(0.0105)
Municipal KPS*After-reform	0.0821^{***}	0.0500^{***}	0.0969^{***}	0.0158	0.0610^{***}	0.0834^{***}
	(0.0113)	(0.0178)	(0.0123)	(0.0142)	(0.0146)	(0.0166)
Obs (RC-years)	1,268	1,556	1,412	1,412	1,402	1,422
R^2	0.821	0.683	0.758	0.725	0.802	0.672
			Panel C: School Federation			
District KPS*After-reform	0.0486^{***}	0.0199^{*}	0.0469^{***}	0.0176	0.0277^{**}	0.0414^{***}
	(0.0116)	(0.0114)	(0.0109)	(0.0126)	(0.0127)	(0.0113)
Municipal KPS*After-reform	0.0907^{***}	0.0611^{***}	0.109^{***}	0.0248^{*}	0.0727^{***}	0.0922^{***}
	(0.0110)	(0.0190)	(0.0125)	(0.0142)	(0.0143)	(0.0174)
Obs (RC-years)	1,304	1,528	1,416	1,416	1,416	1,416
R^2	0.817	0.682	0.766	0.722	0.804	0.672
			Panel D: "Pure" Re-designation			
District KPS*After-reform	0.0325^{***}	0.0210^{*}	0.0317^{***}	0.00592	0.0205	0.0343^{***}
	(0.0111)	(0.0116)	(0.0110)	(0.0140)	(0.0132)	(0.0116)
Municipal KPS*After-reform	0.0832^{***}	0.0552^{***}	0.0940^{***}	0.00917	0.0597^{***}	0.0875^{***}
	(0.0119)	(0.0183)	(0.0125)	(0.0153)	(0.0155)	(0.0174)
Obs (RC-years)	1,342	1,562	1,452	1,452	1,452	1,452
R^2	0.814	0.684	0.759	0.717	0.797	0.671

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 over time. 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. Note that a few ordinary primary schools classified on the basis of the objective

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

historical ranking are now reclassified as first class under the subjective but more up-to-date 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 schools 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 11 presents the MDID results using the Nearest Neighbour strategy based on the new classification, using the sample of residential complexes with an available parental subjective ranking. Consistent with Table 8, it clearly shows that the house prices of RCs which gain access to a first-class school increase significantly by about 5%, 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 11: Matching Differences-in-differences estimates, alternative school classification

	All	**Multi-school dicing**	**School federation**	**"Pure" re-designation**
	(1)	**(2)**	**(3)**	**(4)**
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)
After-reform	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. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Finally, we test the robustness of our findings using an alternative objective classification of school quality based on the number of awards as reported in Table 1. Due to the relatively small number of schools with any awards, we are unable to get precise estimates along the intensive margin. Table 12 shows that RCs in ordinary primary school catchment areas which are re-assigned to a quality school (as proxied by having **any** award) will see a housing premium between 2.5-3.7%, depending on the channel. This is fully consistent with our main findings.

Table 12: Robustness checks with different classifications with medals

	All **(1)**	**Multi-school dicing** **(2)**	**School federation** **(3)**	**"Pure" re-designation** **(4)**
School with awards	0.0608***	0.0836***	0.0772***	0.0720***
	(0.0159)	(0.0169)	(0.0168)	(0.0165)
After-reform	0.233***	0.226***	0.227***	0.227***
	(0.00688)	(0.00711)	(0.00708)	(0.00692)
School with awards # After-reform	0.0342***	0.0306***	0.0369***	0.0254**
	(0.0104)	(0.0106)	(0.0109)	(0.0103)
Observations	3,814	3,432	3,458	3,594
R-squared	0.802	0.803	0.803	0.800

Notes: The schools are grouped into two groups depending on whether having medals, see Table 1. 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 changes 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 school 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 4-8%, 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 increases 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 two alternative measures of primary school prestige based on an up-to-date unofficial ranking from a popular parenting support website, or the number of awards won 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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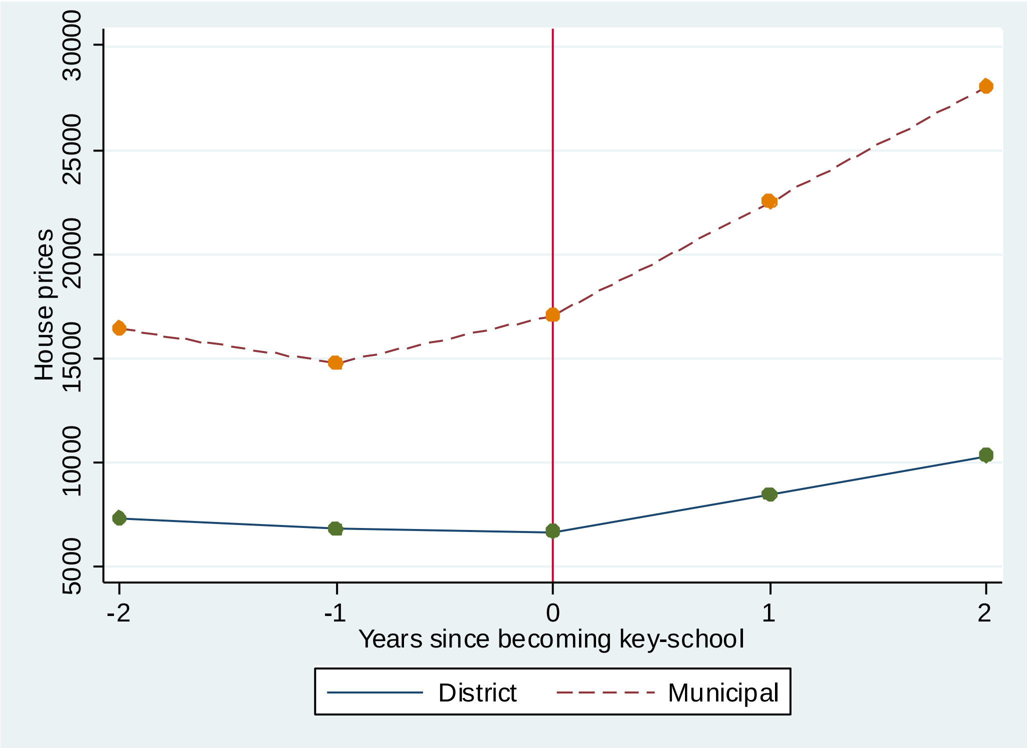
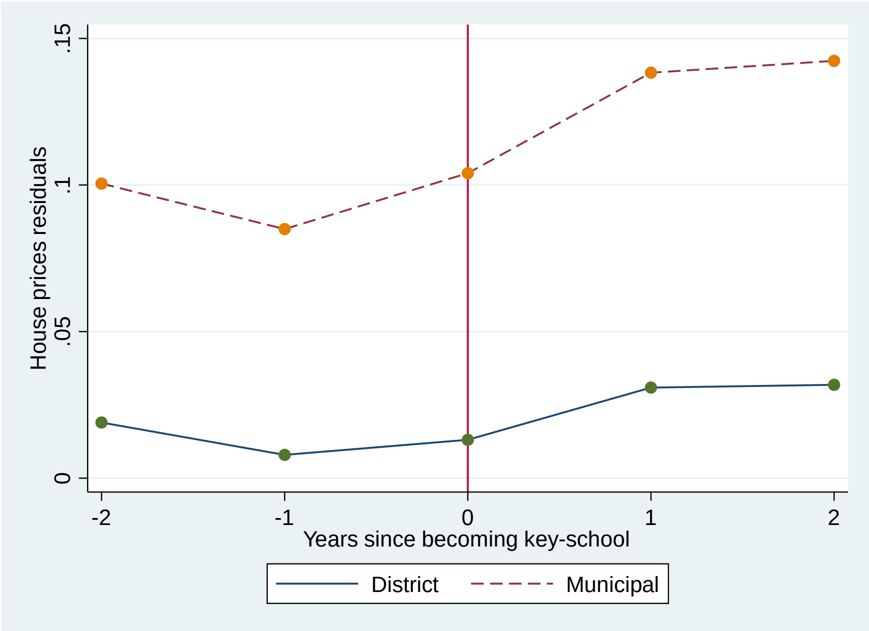
Appendix A:

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



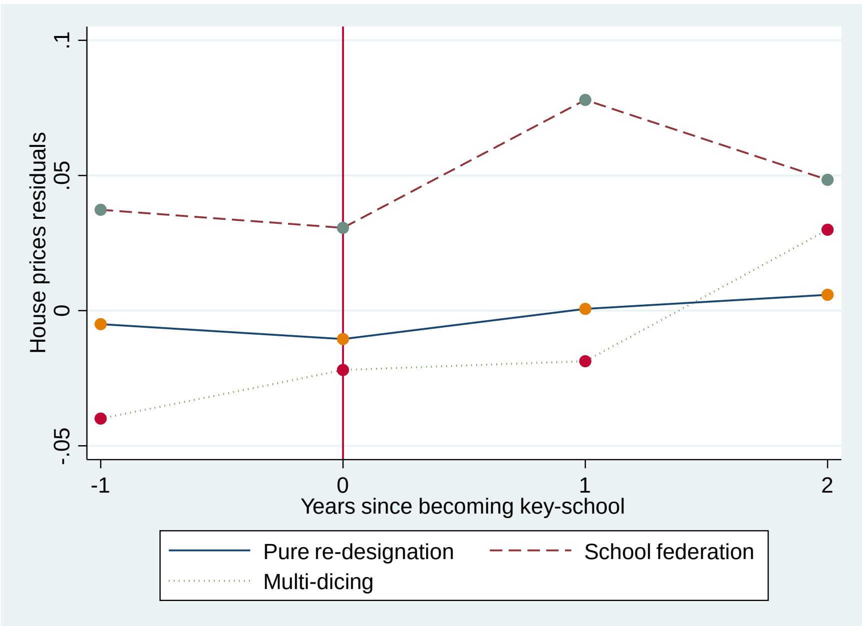
Notes: The vertical axis show the real price premiums of the treated group by key school level, relative to the control group of all RCs affiliated with ordinary schools only over time. Compared to Figure 2, the control group now excludes all RCs affiliated with pre-existing key schools.

Figure A2: Residuals of hedonic regression of house prices by levels.



Notes: The residuals are estimated from hedonic regression of house prices. The control variables are the same as Table 5, column 1.

Figure A3: Residuals of regression of house prices by routes



Notes: The residuals are estimated from hedonic regression of house prices. The control variables are the same as Table 5, column 1.

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

	Full Sample	Multi-school dicing	School federation	Pure re-designation
	(1)	(2)	(3)	(4)
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. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

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.

Appendix B: Goodman-Bacon Difference-in-Differences (DID) decomposition

The canonical DID is restricted to a two-period setting. Therefore, the identification of the treatment effect is theoretically ambiguous when treatment timing varies. Recent research has attempted to extend the canonical DID to a more general setting, by allowing lagged adoption of treatment (Athey and Imbens, 2018) and time-varying treatment (Goodman-Bacon, 2018). In our panel dataset, RCs are assigned to key schools in different years between 2013 and 2016, suggesting that the RCs receive treatment in different time. The natural empirical strategy of interacting treatment status and timing variables is ambiguous in relation to control groups. Bacon (2018) argues that the treatment effect of DID with varying time could be decomposed into a weighted average of all possible 2x2 DID estimators. For instance, the treatment sample in later years could use observations receiving treatment in early years as a control group.

Following Goodman-Bacon et al. (2019) which has demonstrated an example of decomposition in a three-period setting, we show that our canonical DID treatment effect could be regarded as the weighted average of four 2x2 treatment effects.

$$y_{it} = key_i + year_t + \beta^{DD} key_i * year_t$$

$$\beta^{DD} = S_{K_{2014},C}\beta^{2x2}_{K_{2014},C} + S_{K_{2015},C}\beta^{2x2}_{K_{2015},C} + S_{K_{2014},K_{2015},}\beta^{2x2}_{K_{2014},K_{2015},} + S_{K_{2014},K_{2015}}\beta^{2x2}_{K_{2014},K_{2015}}$$

$\beta^{2x2}_{K_{2014},C}$ and $\beta^{2x2}_{K_{2015},C}$ are estimated separately based on the treated RCs assigned to key schools in 2014 and 2015 respectively and RCs with ordinary school form the control group in this subset. $\beta^{2x2}_{K_{2014},K_{2015}}$ is estimated using RCs which are assigned to key schools in 2014 and RCs assigned to key school in 2015 will form control group. $\beta^{2x2}_{K_{2014},K_{2015}}$ is similar to the previous coefficient and estimate the treatment effect of RCs assigned to key schools in 2015 and RCs which receive treatment in 2014 form the control group. Note that we don't include the RCs assigned key school in 2016 because the vast majority of RC re-designations took place in 2014 and 2015.

Table B1 presents the Goodman-Bacon decomposition, suggesting that our two-period canonical DID results are mainly driven by the RCs for which the designated schools switch from ordinary to municipal key primary schools at various points in the sample period, as denoted by Never vs. timing in the table. We suspect that the insignificance of results for all KPS or District KPS might arise from the exclusion of RCs treated in 2016.

Table B1: Goodman-Bacon DID decomposition

VARIABLES	logave_price	Groups	Coefficients	Total weight
Key	0.00206	Timing groups	-0.00606	0.014693
(Obs, 7,576)	(0.00785)	Always v timing	-0.00827	0.419592
		Never v timing	0.010473	0.56562
District key	-0.0119	Timing_groups	-0.00072	0.012788
(Obs, 6,468)	(0.00804)	Always_v_timing	-0.02059	0.330119
		Never_v_timing	-0.00716	0.656923
Municipal key	0.0558^{***}	Timing_groups	0.000521	0.004497
(Obs, 5,160)	(0.0166)	Always_v_timing	0.033175	0.191025
		Never_v_timing	0.061118	0.804459

Notes: The results for District key and Municipal key exclude District key school residential complex and Municipal key school residential complex respectively. The sample is restricted to RCs which changed designated school in 2014 and 2015. The following figures are the corresponding results of each decomposition. The control variables are consistent with Table 5. Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure B1, B2 and B3 visualise the Goodman-Bacon decomposition for all KPS, district-level KPS and municipal-level KPS, respectively. Consistent with Table B1, the patterns suggest that our two-period canonical DID results are mainly driven by the RCs for which the designated schools switch from ordinary to municipal key primary schools at various points in the sample period (denoted as "never treated vs timing" in the figure).

Figure B1: Bacon-decomposition, All Key Schools

key

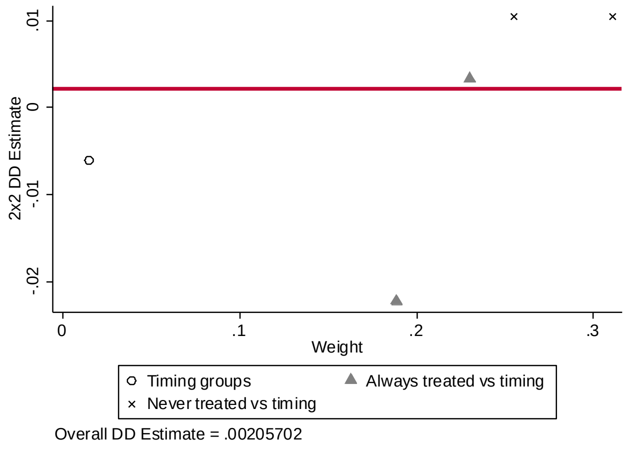


Figure B2: Bacon-decomposition, District-level Key Schools

District key

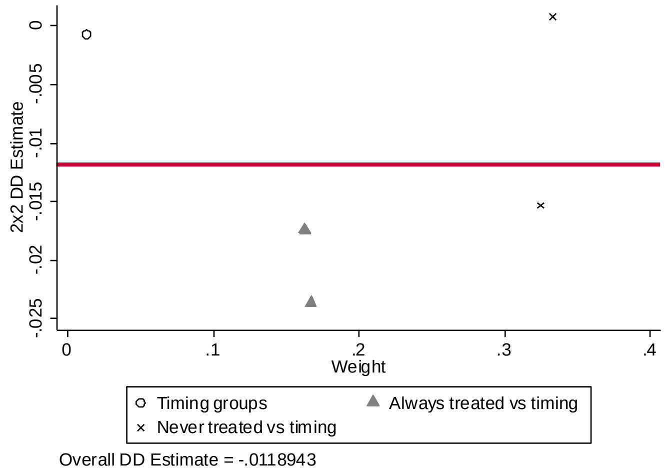


Figure B3: Bacon-decomposition, Municipal-level Key Schools

Municipal key