Down Payment Requirements and House Prices: Quasi-Experiment Evidence from Shanghai *

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Abstract

Using the regression discontinuity design, a quasi-experiment approach, this paper establishes a causal relationship between the down payment requirement and house prices by exploiting a unique institutional background in Shanghai. In the unique setting, the required minimal down payment ratio jumps at the Inner Ring, a circular elevated highway, from 50% to 70% for a large group of buyers. With transaction level data from the largest real estate broker in Shanghai, we find that a lower required down payment ratio increases the apartment price by 138.8 thousand RMB, around 3.71% of the average transaction price.

Keywords: Housing Price, Down Payment, Credit Policy, Regression Discontinuity
JEL Codes: G12; G28; O18; R21; R28

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1. Introduction

Since the Great Financial Crisis, macroprudential policy has attracted growing attention. As one macroprudential policy tool, adjusting the down payment requirement is often used by governments worldwide to counter housing price movements.[1] Despite its popularity, the effectiveness of adjusting down payment requirements on housing prices remains unclear. One major challenge is that variations in down payment requirements are hardly exogenous. Governments move the required down payment ratio for a reason. They lower the ratio during housing busts and raise it during housing booms. Therefore, observing a housing price increase after a raised required down payment ratio does not necessarily imply that the down payment requirement policy is impotent. Instead, it simply shows the problem endogeneity can create in identification.

Our paper circumvents the endogeneity problem by employing a quasi-experimental approach, the regression discontinuity (RD) design. Using the housing transaction data, we are able to achieve a clean identification leveraging a unique institutional setting in Shanghai: a differential credit policy. This differential credit policy treats different types of apartments differently. It imposes a smaller minimum down payment ratio on an ***ordinary*** apartment relative to an ***above-ordinary*** one.

An apartment must meet certain criteria to be considered as ordinary.

[1] For reference, please see Kuttner and Shim (2016).

Starting from Nov 20th, 2014, an apartment is classified as an ordinary apartment if it meets all the following criteria: the apartment is less than $140m^2$; the total price is less than 4.5 million RMB if it is within the Inner Ring of Shanghai, or the total price is less than 3.1 million RMB if it is between the Inner Ring and the Outer Ring, or the total price is less than 2.3 million RMB if it is outside the Outer Ring. These criteria have not been modified until the time when our paper is written (March 2023). Figure 1 presents a map of Shanghai with three circled elevated highways: the Inner Ring[2], the Middle Ring, and the Outer Ring.

Following the definition, an apartment with price between 3.1 million and 4.5 million RMB and size smaller than 140 m^2 is labeled as an ordinary apartment if it is located within the Inner Ring. However, the same apartment is an above-ordinary one if it is outside the Inner Ring. For repeated buyers, the minimal down payment ratio is 50% if the apartment to purchase is an ordinary one, but the minimal ratio is as high as 70% if the apartment is above ordinary. How will the difference in minimum down payment ratio affect the price of an ordinary apartment relative to an above-ordinary apartment with similar quality? We employ a RD design to explore the discontinuity at the Inner Ring, and we will discuss later why we do not exploit discontinuity at other dimensions, such as 140 square meters in size or 4.5 million in price. We find that the differential

[2] For a reference of the Inner Ring, please visit: https://en.wikipedia.org/wiki/Inner_Ring_Road_(Shanghai).

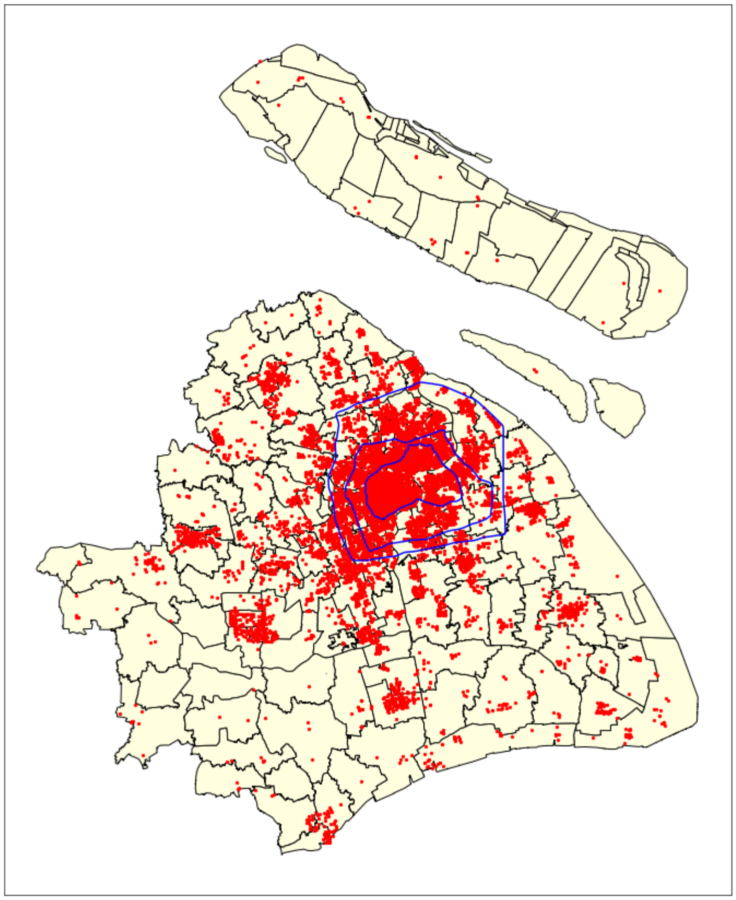

Figure 1: *A map of Shanghai*

Notes: *A map of Shanghai. From inside to outside, the rings are the Inner Ring, the Middle Ring, and the Outer Ring. Each red dot represents a residential block for which we have transaction data.*

credit policy raises ordinary apartments prices by about 138.8 thousand RMB, which is around 3.71% of the average price.

We perform several additional tests which support that our estimated premium does come from a lower down payment requirement associated with ordinary apartments rather than some social status effect (Coffee et al., 2020) associated with the Inner Ring. First, for an apartment whose price is below 3.1 million, it is considered as ordinary regardless of its relative location to the Inner Ring; if an apartment's price is above 4.5 million, it is consider as above-ordinary no matter whether it is inside or outside the Inner Ring. If the premium does come from a lower down payment requirement, we should expect no price premium for apartments inside the Inner Ring whose prices are above 4.5 million RMB or below 3.1 million RMB. We perform the same RD estimations for groups in these two price ranges and find no premium on houses inside the Inner Ring. Second, whether a house is labeled as ordinary depends on the location relative to the Inner Ring and Outer Ring, but not the Middle Ring. So, there should be no price premium for those apartments within the Middle Ring. However, if there is some social status effect associated with the rings, we should observe such a premium. We test for the price discontinuity at the Middle Ring and find no significant premium of houses inside it, which further excludes the social status effect. Third, we perform an pre-policy analysis on the 3.1-4.5 million price range sample before the differential credit policy is implemented. At that time apartments inside the Inner Ring enjoy the same minimum down payment ratio as those outside the Inner Ring. We find no significant price premium at that time. These findings support that our estimated premium comes from the advantage of being ordinary apartments in the credit policy.

Our paper provides new evidence on the effects of down payment ratio on housing prices. Our estimated price premium, 3.71%, arises from the relatively greater credit availability associated with ordinary apartments over above-ordinary apartments, holding the total credit supply in the whole economy fixed. If the government were to lower the down payment ratio for all transactions, the overall credit supply would increase and the housing price response should be much larger than the case in which the total credit supply is fixed.

It is also worth noting that our estimation is based on data from the Shanghai market, and the estimated price premium is contingent on the level of required down payment ratio in this specific market. Compared with the US and other countries, China has a relatively high required down payment ratio. The down payment ratio for first-time buyers is at least 30% in most cities, while the average down payment ratio in US may be less than 10%. Our estimation can be different if the average down payment ratio is at a different level.

To our best knowledge, our paper is the first to investigate the effects of a differential credit policy on housing prices. This differential credit policy has an important redistribution effect, transferring wealth from owners of above-ordinary apartments to owners of ordinary apartments, by raising the relative prices of ordinary ones. Therefore, this discriminative credit policy induces an arbitrary price wedge between two apartments of similar quality and leads to potential welfare loss.

Our paper fits into a growing strand of literature exploring the relationship between credit supply and housing prices. Our study stands out due to the quasi-experimental approach and the transaction level data within a city. Using historical or regional data, Jordà et al. (2016), Mian and Sufi (2009), Mian and Sufi (2022), and Chen et al. (2020) show the importance of credit supply on housing prices. Dursun-de Neef (2019), Favara and Imbs (2015), and Vigdor (2006) hunt for exogeneous variations in the credit supply to make causal inferences about credit supply and housing prices.[3] Unlike these papers which explore the cross-country or regional variations, we use transaction level data to exploit the discontinuity in the credit availability across a geographic border. The major advantage of our study is the quasi-natural experiment setting, which assures the exogeneity of the credit availability and a clean identification of the effect of credit availability on asset prices. Tzur-Ilan (2023) is a recent paper which also uses micro level data, but it employs a difference-in-difference matching approach to study the effects of Loan-to-Value policy on housing choice in Israel.

Our paper adds empirical evidence complementing the theoretical literature studying the effects of down payment requirements. The seminal

[3] Dursun-de Neef (2019) uses the heterogeneity in the amount of long-term debt that matured right after the onset of the 2007-09 crisis to measure the variation in banks' exposure to liquidity shock and thus reduction in loan supply. Favara and Imbs (2015) use regional variations in banking deregulation to identify the effects of the credit supply on housing prices. Vigdor (2006) use the regional share of purchases by veterans to proxy the credit supply since the Veteran's Administration mortgage program grants the veterans a privileged zero down payment.

work by Stein (1995) shows that down-payment constraint explains many features of the housing market, for instance, the intense trading volume and large price fluctuations. Ortalo-Magne and Rady (2006) propose a life-cycle model depicting people climbing up the property ladder. Their results suggest that income shock to the credit constrained owners could generate a similar set of stylized facts about the housing market. Kiyotaki et al. (2011), Sommer et al. (2013), and Favilukis et al. (2017) presents quantitative models discussing the effects of different policy rules which include the down payment ratio policy. Our paper provides empirical evidence supporting the theoretical importance of down payment requirements.

Another strand of the literature emphasizes the heterogeneity of housing markets. Many researchers focus on segments of housing markets, and they study heterogeneous effects of credit supply on housing prices. Housing market segments may be defined on geographic areas. For instance, Benito (2006) shows that house prices within a district are more sensitive to shocks if that district has a high leverage. The segments may also be defined on buyers' identity. Duca et al. (2011) present empirical evidence that credit standards for first-time buyers significantly affect house prices. Landvoigt et al. (2015) use transaction data from San Diego to show that the credit expansion for first-time buyers contributed to the boom of 2002–2005 in the United States. Within the Shanghai housing market, we focus on the differential credit policy targeting at repeated buyers and explore its impact on housing prices in different geographic areas. In the spirit of focusing on policies targeting certain segments of a housing market, our paper is closet to the work of Han et al. (2021). They investigate effects of different loan-to-value ratio caps for different segments of a housing market with quite a different institutional background in Canada. We are unique in exploiting the discontinuity at a geographic boundary, which facilitates the identification of a causal effect.

Our paper is organized as follows. First, we introduce the details of the unique institutional background and an illustrative the economic framework in Section 2; Section 3 describes the transaction level data and explains our empirical strategy; Section 4 presents the estimation results with placebo tests and robustness checks. In Section 5, we conduct some additional tests, such as examining other dependent variables. The last section concludes our paper.

2. Institutional Background and Economic Framework

2.1. Institutional background

The Chinese housing market experienced several ups and downs after the Great Financial Crisis. The municipal government of Shanghai implemented several policies to buffer the housing market fluctuations.[4] Figure 2 shows the related policies since 2010.

[4] Zhou (2016) provides a detailed summary of these housing market policy interventions until March 2015.

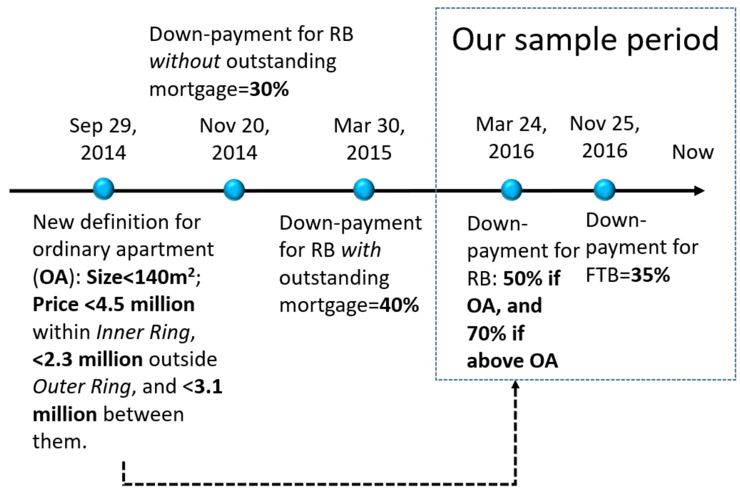

Figure 2: *Policy timeline*

During this time period, the government implemented a differential credit policy that favors first-time buyers and ordinary apartments. Before 2016, the government only requires a smaller down payment ratio for first-time buyers, regardless of the type of the apartment. Starting from 2016, the government sets different down payment ratios for ordinary and above-ordinary apartments. A repeated buyer needs to pay a 70% of the total price as the down payment if she buys an above-ordinary apartment, and only a 50% down payment if she buys an ordinary one. Repeated buyers are those who either own an apartment in Shanghai or have a mortgage record in any city in China, even if the mortgage loan has been paid off. This broad classification for repeated buyers (including those with a mortgage record) makes this policy affect a relatively large fraction of buyers. As a comparison, a first-time buyer must pay at least 35% of the housing price as a down payment, regardless of the apartment type.

How will the credit policy affect the housing price? Suppose there exist two apartments with the same quality sell at 4 million were there no such differential credit policy. They are both less than 140 square meters, and they are both very close to the Inner Ring. Apartment A is inside the Inner Ring, while Apartment B is outside the Inner Ring. After the differential credit policy is implemented, Apartment A will be classified as an ordinary apartments, and Apartment B will be classified as an above-ordinary apartment. For a repeated buyer, she needs at least 2 million RMB as a down payment for Apartment A and 2.8 million RMB for Apartment B. The difference in down payment equals 0.8 million RMB.[5] If buyers are liquidity constrained, Apartment A will sell at a higher price than Apartment B. This is clearly illustrated in the following subsection.

2.2. Economic framework

We provide a simple conceptual framework to show that the minimum down payment requirement affects housing prices. Similar models can be found in Favilukis et al. (2017) and Zevelev (2021).

The households buy an apartment with a down payment constraint $1-\kappa$, i.e., they can borrow a κ fraction out of the apartment value. The

[5] As a reference, the Municipal Statistics Bureau of Shanghai reports that the annual disposable income per capita in Shanghai is 57692 RMB in 2016 and 82429 RMB in 2021. Comparing these numbers with the difference in down payments (0.8 million), it seems that the credit advantage would matter for a large proportion of households.

households buy the apartment at $t = 0$, hold the apartment at $t = 1$, and sell the apartment to pay back the loan at $t = 2$.

The household maximizes:

$$U = u(c_0, h) + \beta \cdot u(c_1, h) + \beta^2 \cdot c_2$$

subject to

$$\begin{aligned} c_0 + p_0 \cdot h &\leq y_0 + b \\ c_1 + r_0 \cdot b &\leq y_1 \\ c_2 + b &\leq y_2 + p_2 \cdot h \\ b &\leq \kappa \cdot p_0 \cdot h \end{aligned}$$

where (c_t, y_t, h, b) are the consumption, income, size of apartment, and the size of mortgage at $t = 0$, respectively. r_0 is the mortgage interest rate. The households only pay the interest at $t = 1$ and the principal at $t = 2$. We assume that the household sticks to the original housing choice, which is justified by the large adjustment cost of rescaling their apartments' size, and that there is no depreciation of the house.

The households' first order conditions can be rearranged as

$$p_0 = \frac{1}{\lambda_0}\left(\underbrace{(1+\beta)\cdot u_h}_{\text{housing service flow}} + \underbrace{\mu_0 \cdot \kappa \cdot p_0}_{\text{collateral value}} + \underbrace{\lambda_2 \cdot p_2}_{\text{resale value}}\right). \tag{1}$$

λ_t is the marginal utility of consumption at t, and μ_0 is the shadow value of marginally relaxing the collateral constraint.[6] We can rewrite p_0 as the following:

$$p_0 = \frac{(1+\beta)\cdot u_h + \lambda_2 \cdot p_2}{\lambda_0 - \mu_0 \cdot \kappa}. \tag{2}$$

In the Appendix A.1, we provide an argument that apartment price p_0 increases with κ. Our illustrative model suggests that conditional on all other variables, an apartment with a higher credit availability should sell at a higher price.

3. Data and Estimation

We use transaction level data from Lianjia, a real estate broker with the largest market share in Shanghai.[7] To check the representativeness of our data, we compare the transaction volume of our data with the official transaction volume from the Municipal Statistics Bureau of Shanghai. For example, there were 30,961 transactions through Lianjia in 2018. The total number of transaction in the same year was 163,930 according to

[6] If a household has a binding constraint that $b = \kappa \cdot p_0 \cdot h$, then $\mu_0 > 0$ due to the KKT condition.

[7] For reference, please visit their website at https://sh.lianjia.com/.

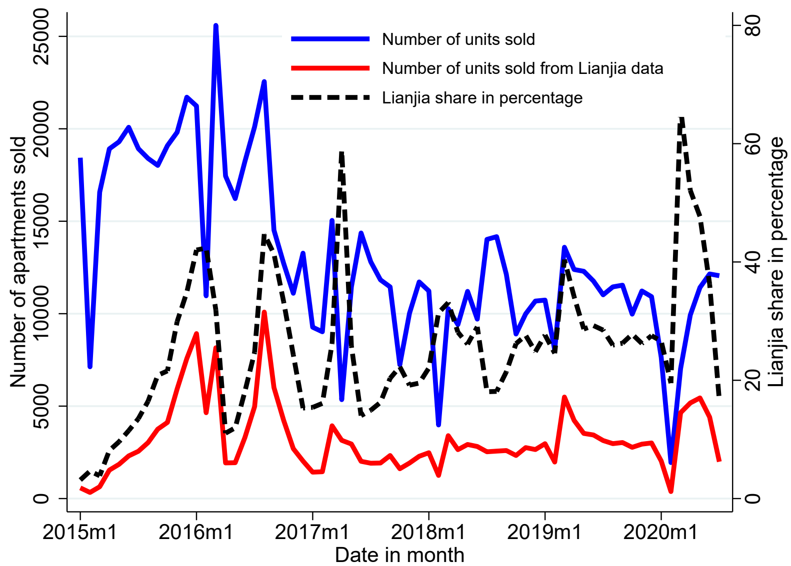

Figure 3: *Lianjia data and the official data*

Notes: *The blue line is the total number of units sold in Shanghai, and the red line is the total number of units sold through Lianjia. Both are on the left scale. The dash line on the right scale is the market share in percentage for Lianjia.*

Wind, which is a Chinese counterpart of Bloomberg. So Lianjia's market share was around 19% in 2018. Figure 3 presents time series for the two transaction volumes mentioned above and the market share for Lianjia.[8]

For each transaction record, we have the information on the transaction date, the residential block name, and the apartment's physical attributes such as the apartment size in square meters, the apartment age, the number of bedrooms and living rooms, a discrete variable for the decoration level, the relative floor indicator, the total number of the building floors, the building type, and the listing price. As for the geographical data, we manage to get the latitude and longitude data for each residential block, each primary school, and each subway station. We use the exact location of each residential block to identify the nearest subway station and then compute the distance to its nearest subway station. Besides, we manually match each block to its primary school assigned by the government and compute the distance from the block to its matched primary school. To control for the school quality, we also include a dummy variable indicating whether the assigned primary school is an exemplary one or a regular one.

The key variable is the distance of apartments to the Inner Ring. Figure 1 shows a Shanghai map with the three rings. Each red dot represents a residential block for which we have GIS location data. As we find GIS

[8] We exclude from our analysis the commercial-residential apartments, which are treated differently from residential apartments by tax policies, credit policies, and property laws. We also exclude rural houses, which cannot be freely traded.

location data for the rings, we then calculate in kilometers the distance from each block to the rings. Apartments in the same block have the same distance to a specific ring. We define negative distances if the block is outside a ring. For example, if an apartment's distance to the Inner Ring is -1, it implies that the apartment is 1 km outside the Inner Ring.

Table 1: *Summary statistics*

	Full Sample		Treatment Group		Control Group		Difference
	Mean	SD	Mean	SD	Mean	SD	Control-Treatment
Dependent Variables							
Total price in 10K	376.58	260.64	378.88	40.63	366.38	41.29	-12.50***
Listing price in 10K	388.00	288.99	387.61	55.74	374.93	52.17	-12.68***
Running Variable							
Distance to the Inner Ring in km	-8.67	9.55	0.33	0.18	-0.37	0.19	-0.70***
Covariates							
Size in square-meter	75.66	34.74	54.67	11.13	62.59	12.82	7.92***
Apartment age	18.51	10.13	27.61	8.17	26.92	7.79	-0.69*
Number of rooms	3.26	1.18	2.68	0.66	2.91	0.62	0.24***
Number of bedrooms	1.94	0.76	1.75	0.53	1.93	0.47	0.18***
Number of livingrooms	1.31	0.62	0.92	0.48	0.98	0.42	0.06***
Level of decoration	1.14	1.31	1.23	1.31	1.17	1.29	-0.07
Facing east	0.03	0.16	0.06	0.23	0.08	0.27	0.02
Facing south	0.88	0.32	0.85	0.36	0.91	0.28	0.06***
Facing west	0.02	0.14	0.06	0.23	0.04	0.19	-0.02*
Facing north	0.09	0.29	0.10	0.29	0.05	0.22	-0.04***
Distance to the assigned primary school	0.54	0.49	0.29	0.18	0.32	0.18	0.03***
Distance to the nearest subway station	1.29	1.75	0.50	0.22	0.59	0.25	0.08***
High quality school district	0.51	0.50	0.48	0.50	0.48	0.50	-0.01
Distance to People's Square	14.91	9.74	5.45	1.64	6.86	1.32	1.41***
Observations	128139		1599		1023		2622

Notes: *The full sample includes transactions from Mar 2016 to Dec 2019. The treatment group are those apartments with size less than 140 square meters, transaction price between 3.1 million and 4.5 million RMB, and within 0.68km (the optimal bandwidth) inside the Inner Ring, while the control group are those within the same size range and price range but within 0.68km outside the Inner Ring. The last column is the difference of the control group minus the treatment group. * indicates significance at 10%, ** at 5%, and *** at 1%.*

We show the summary statistics in Table 1. Our sample covers 128,139 transactions in total from March, 2016 to December, 2019; the average price is 3.77 million RMB; the average size is slightly less than 76 square meters; the number of rooms is around 3.3; the assigned primary school is around 540 meters away; and the nearest subway station is 1,290 meters away.

We will later focus on transactions near the Inner Ring as we adopt a local polynomial approximation approach in RD estimation proposed by Lee and Lemieux (2010). Figure 4 shows the blocks which are used in our RD estimation. We present the subsample statistics for those transactions within 0.68 km (the optimal bandwidth) on both sides of the Inner Ring. The treatment group consists of those apartments with size less than 140 square meters, within the price range between 3.1 million RMB and 4.5 million RMB, and within 0.68km inside the Inner Ring, while the control group consists of those apartments with the same size range and price range but within 0.68km outside the Inner Ring.

3.1. Estimation

To form a causal inference of down payment ratios on housing prices, we employ the RD design (Hahn et al. (2001), Imbens and Lemieux (2008)) method which exploits a discontinuity in the treatment assignment to identify a causal effect. Specifically, we consider the following specification

Figure 4: *Residential blocks used for RD estimation around the Inner Ring*

Notes: *The black line is the Inner Ring, and the red dots are those residential blocks used in the main RD estimation. The Huangpu River runs across the Inner Ring, and the Century Park intersects with the Inner Ring. Besides, the Zhangjiang Hi-Tech Park and the Shanghai New International Expo Center are next to the southeast corner of the Inner Ring. Due to these reasons, there are some sections along the Inner Ring where there are no apartments within 0.68 km to the Inner Ring.*

for estimating the RD treatment effect

$$y_i = \beta_0 + \tau m_i + \beta f(x_i) + \gamma m_i f(x_i) + \Gamma' Z_i + \epsilon_i, \qquad \forall x_i \in (-h, h). \tag{3}$$

y_i is the total price, and the running variable x_i is the distance to the Inner Ring. We cluster the standard errors at the residential block level. The treatment group ($m_i = 1$) are those inside the Inner Ring ($x_i > 0$), and the control group are those outside the Inner Ring ($x_i < 0$).[9] The treatment assignment follows a known deterministic rule, $m_i = \mathbb{1}\{x_i > 0\}$, where $\mathbb{1}\{\cdot\}$ is the indicator function.

$f(x_i)$ is a function of the distance to the Inner Ring, and it is to capture the effects of the distance to the Inner Ring on the apartment price. γ is to allow asymmetric effects for the distance to the Inner Ring from inside and outside the Inner Ring. Z_i is a vector of covariates that affect the apartment price, including the apartment size, the squared size, the apartment age, the squared apartment age, the number of rooms, dummy variables for decoration level, the distance to the assigned primary school and the nearest subway station, the school quality, and the distance to People's Square (the city center of Shanghai). These are the commonly used variables in hedonic pricing model.

We adopt a local polynomial approximation approach proposed by Lee and Lemieux (2010) in which the estimation is based on observations within a certain range of the running variable ($x_i \in (-h, h)$). It is well-acknowledged in the RD literature that the selection of bandwidth (h) is crucial for the estimation, and the choice of bandwidth reflect the common tradeoff between estimation bias and estimation variance. We apply the optimal bandwidth selection following data driven procedure by Calonico et al. (2014).[10]

[9] There are no apartments with $x_i = 0$

[10] Let $MSE = Bias^2 + Variance$; traditionally, the MSE-minimized bandwidth will be

The parameter τ captures our interest as it measures the discontinuity jump in the transaction price at the Inner Ring. We present our estimates $\hat{\tau}$ in tables with three panels and four columns. Each column corresponds to a different model specification. Gelman and Imbens (2019) suggests that higher order polynomials are not suitable, so we take the linear model with controls as the baseline specification (Column 2). However, we also report the results using the other three models for comparison purpose: a linear model for $f(x_i)$ without controls (Column 1), a quadratic model for $f(x_i)$ with controls (Column 3), and a cubic model for for $f(x_i)$ with controls (Column 4).

Multiple panels are there to contrast our main estimate with estimates from comparison groups. In the main RD estimation we have to restrict our sample to those apartments between 3.1 million to 4.5 million and less than 140 m^2 (Panel A for all tables). Only in this restricted sample, being inside the Inner Ring is sufficient and necessary for apartments to be ordinary. Thus, $\hat{\tau}$ in Panel A captures the price premium caused by a lower down payment associated with ordinary apartments. We do perform similar estimations for two other samples for comparison. First, we perform the same estimation for apartments below 3.1 million RMB and less than 140 m^2. These apartments are labeled as ordinary apartments independent of its location to the Inner Ring. Results are reported in Panel B. Second,

the optimal bandwidth. Calonico et al. (2014) further extend this method to include covariate adjustment, heteroscedasticity-robust or cluster-robust variance, etc.

we repeat the exercise for apartments above 4.5 million RMB which are labeled as above-ordinary regardless of their location to the Inner Ring. Results are reported in Panel C. Since the down payment requirement for houses in these two groups does not depend on the location relative to the Inner Ring, such houses can be used for placebo tests regarding the price impact of the differential credit policy. If there is any social status effect associated with house locations inside the Inner Ring, it should be captured by $\hat{\tau}$s in Panel B and C.

Before we present our estimation results, we present the regression discontinuity plot first. Figure 5 depicts the total apartment price around the Inner ring in the range of 1 km on each side with a bin size of 0.2km. We draw the graphs for four groups: (1) the full sample, (2) the sub-sample with price between 3.1-4.5 million RMB and size less than 140 m^2, (3) the sub-sample with price less 3.1 million and size less 140 m^2, (4) the sub-sample for those with price larger than 4.5 million. Zero on the x-axis indicates the Inner Ring; $x_i > 0$ indicates being inside the Inner Ring; and $x_i > 0$ indicates being outside the Inner Ring. The only significant discontinuous jump in price is in the sub-sample (2) in which on the right hand sides to zero are ordinary apartments and on the left hand side are the above-ordinary apartments. In sub-sample (3) both sides to zero are ordinary apartments, and in sub-sample (4) both side to zero are above-ordinary apartments. There exists no significant price jump in (1), (3), or (4).

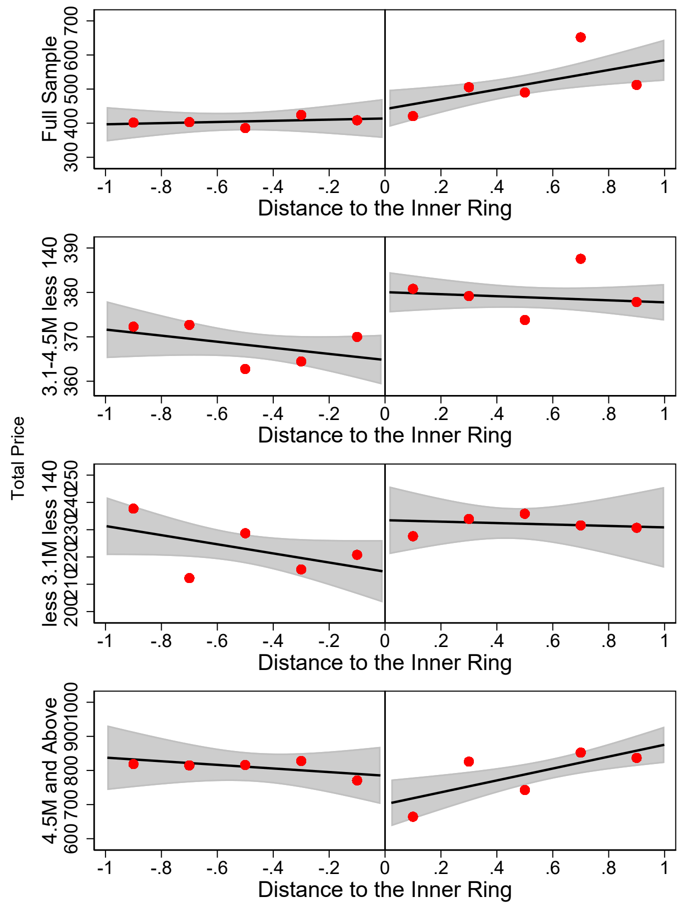

Figure 5: *Regression discontinuity plot at the Inner Ring*

Notes: *Each circle is a binned average of 0.2km. The solid line represents the predicted values of a local linear model estimated using raw data on each side of the Inner Ring, clustered at the residential block level. The shaded area is the 95 percent confidence intervals. The top figure is for the full sample, the second is for those with price between 3.1-4.5 million and size less than 140* m^2*, the third is for those with price less 3.1 million and size less 140* m^2*, the last is for those with price larger than 4.5 million.*

Is the price jump caused by jumps in other covariates? Our identification strategy assumes that apartment quality does not jump at the Inner

Ring. To justify this assumption, we show that the covariates are balanced across the Inner Ring for the 3.1-4.5 million RMB (and less than 140 m^2) sub-sample. Figure 6 presents the results. We check the following covariates: the apartment size, the apartment age, number of the bedrooms, number of living rooms, the decoration level, the distance to school, the distance to the nearest subway station, the school quality, and the distance to the city center. No statistical significant discontinuity is detected.

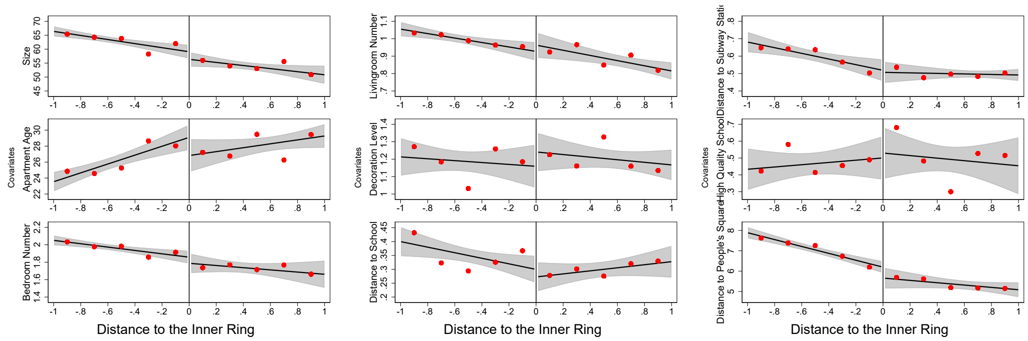

Figure 6: *Balanced covariates checks*

Notes: *Each circle is a binned average of 0.2km. The solid line represents the predicted values of a local linear model estimated using raw data on each side of the Inner Ring, clustered at the residential block level. The shaded area is the 95 percent confidence intervals. We check the following covariates: the apartment size, the apartment age, number of bedrooms, number of living rooms, the decoration level, the distance to school, the distance to the nearest subway station, the school quality, and the distance to the city center:the People's Square.*

We have not yet discuss the choice of the running variable in our setting. In the criteria for ordinary apartments, there are three cutoffs: the price cutoff (4.5 million for apartments within the Inner Ring), the geographical cutoff (the Inner Ring), and the size cutoff (140 squre meters). We focus on the geographical discontinuity at the Inner Ring and choose the distance to the Inner Ring as the running variable for several reasons. First, since our goal is to estimate the price premium of ordinary apartments, using price as the running variable will lead to a regression with price as both the dependent variable and an independent variable. Second, apartment size is not a proper running variable because of the very limited amount of apartments whose size is larger than 140 m^2, price is less than 4.5 million, and location is inside the Inner Ring. Thus, we do not have a control group with sufficient observations. The advantage of using distance to the Inner Ring is clear because it is a precise measure and the geographical location cannot be manipulated.

Is there a way to manipulate the data to get some above-ordinary apartments being classified as ordinary apartments? For the three cutoffs in the definition of ordinary apartments, households have no way to manipulate the location of the apartment (related to our running variable), and they have no way to manipulate the size of the apartment as it is recorded in the government's information system when the apartment was built. As for price, what we have is the actual transaction price recorded by the brokerage, which is unlikely to be manipulated. In China, it is possible for traders to report another different price to the government and the bank which issues the mortgage, which will determine the minimum down payment requirement. So, if there is any excess bunching in price, it should be more associated with the price reported to the government and banks, rather than the price privately recorded by the brokerage (our data). We confirm the absence of excess bunching in the price recorded by the brokerage following estimation as in Chetty et al. (2011), and we cannot reject that there is no excess bunching at the cutoff of 4.5 million for apartments inside the Inner Ring (Appendix A.2).

4. Results

We present our main results in this section followed by a placebo test at the Middle Ring, the pre-policy results at the Inner Ring, and some robustness checks.

4.1. Main Results at the Inner Ring

We present the regression discontinuity estimates at the Inner Ring in Table 2. In each panel we report the estimate, followed by the conventional z value, the robust-adjusted z value as a reference, the optimal bandwidth, and the number of effective observations as Calonico et al. (2014) suggests. Panel A shows our main result, and Column 2 is the baseline model. Conditional on apartment's characteristics, an ordinary apartment sells 138.8

thousand more than an above-ordinary apartment with similar characteristics. The average price for those apartments used in the estimation is 3.74 million, and 138.8 thousand is approximately 3.71% of the average price. The four columns in Table 2 correspond to different model specifications as discussed above,[11] and the estimated premium are all significant and quite robust across specifications ranging from 138.8 thousand RMB to 170.0 thousand RMB (excluding the no covariates setting). We attribute this price premium to the lower required down payment ratio for ordinary apartments.

Some may have concerns that the Inner Ring itself can account for this premium. Following this logic, we would expect that apartments for all price ranges within the Inner Ring should sell at a higher price than those apartments with similar quality but marginally outside the Inner Ring. We run the same RD estimation for apartments priced below 3.1 million and above 4.5 million, and we find no statistical significant discontinuity as shown in Panel B and C of Table 2. Panel B is for ordinary apartments irrespective of whether the apartment is inside the Inner Ring or not, and Panel C is for above-ordinary apartments. The results in all three panels are against that the Inner Ring itself can bring price premium, while they are consistent with the conjecture that the lower down payment ratio associated with ordinary apartments is the source for the price premium.

[11] They are a linear model without controls, a linear model with controls (benchmark), a quadratic model with controls, and a cubic model with controls.

Table 2: *Main results: Three price groups at the Inner Ring*

	Linear (1)	Linear (2)	Quadratic (3)	Cubic (4)
***Panel A**: Size* $< 140m^2$; $3.1m \leq$ *Price* $\leq 4.5m$ *RMB*				
RD treatment effect	11.94**	13.88**	17.00***	14.66***
Conventional z value	2.30	2.51	2.81	2.91
Robust-adjusted z value	1.71	1.64	2.13	2.10
Bandwidth	0.82	0.68	0.55	0.85
Effective number of observations	3,048	2,442	1,988	3,022
***Panel B**: Size* $< 140m^2$; *Price* $\leq 3.1m$ *RMB*				
RD treatment effect	14.85	3.707	5.979	4.580
Conventional z value	1.33	0.39	0.60	0.52
Robust-adjusted z value	1.09	0.11	1.86	0.51
Bandwidth	1.02	0.68	0.54	0.85
Effective number of observations	7,386	4,727	3,872	5,815
***Panel C**: Price* $> 4.5m$ *RMB*				
RD treatment effect	-87.29	-37.91	-43.57	-32.35
Conventional z value	-1.27	-1.17	-1.19	-1.05
Robust-adjusted z value	-0.92	-1.14	-1.15	-1.17
Bandwidth	1.00	0.85	0.68	1.06
Effective number of observations	6,176	4,904	3,830	6,038
Covariates	NO	YES	YES	YES

Notes: *The sample period is Mar, 2016- Dec, 2019. The running variable is the distance to the Inner Ring, and a positive distance implies that the block is inside the Inner Ring. In each panel, we report the conventional z value in row 2, followed by the robust-adjusted z value, the optimal bandwidth, and the number of effective observations as Calonico et al. (2014) suggests. Column 1 presents the estimates for a linear model without control variables; and Column 2-4 are for linear, quadratic and cubic polynomial fitting with controls. The optimal bandwidth is selected following Calonico et al. (2014). The bandwidth is in kilometers and the estimated premia are in 10-thousand RMB. * indicates significance at 10%, ** at 5%, and *** at 1%.*

Some may be concerned that the transaction price is endogenous, so limiting the RD test's sample to this specific price range potentially leads to estimation bias. In particular, suppose that the better credit availability associated with apartments inside the Inner Ring leads to a price premium. Then cutting the treatment group and the control group with the same upper and lower price bounds actually forces us to compare lower-quality apartments insider the Inner Ring with higher-quality apartments outside the ring. But this would result in underestimation of the premium, rather than overestimation. As we formally readjust the sample, it is the case (Appendix A.3).

4.2. Pre-policy results at the Inner Ring

The differential credit policy, which treats ordinary apartments differently, took place in March 2016, so the price premium should arise after March 2016. We perform a pre-policy estimate using data of 2015. We do not use earlier data because the number of observations in Lianjia's database is very small before before 2015. Lianjia expanded its market share in Shanghai by merging another broker in March 2015. The pre-policy results are displayed in Table 3. Compared with our baseline results in Table 2 Panel A, the estimated premium in the pre-policy period is much smaller (30.11 thousand verses 130.9 thousand) and statistically insignificant. For the two comparison groups, the results are comparable to those in Table 2.

Table 3: *Pre-policy results for the Inner Ring*

	Linear (1)	Linear (2)	Quadratic (3)	Cubic (4)
***Panel A**: Size* $< 140m^2$; $3.1m \leq$ *Price* $\leq 4.5m$ *RMB*				
RD treatment effect	3.636	3.011	2.598	4.726
Conventional z value	0.50	0.45	0.35	0.77
Robust-adjusted z value	0.22	0.12	0.12	-0.13
Bandwidth	1.03	1.05	0.84	1.31
Effective number of observations	1,196	1,045	834	1,268
***Panel B**: Size* $< 140m^2$; *Price* $\leq 3.1m$ *RMB*				
RD treatment effect	3.557	6.237	8.145	6.440
Conventional z value	0.25	0.74	0.86	0.84
Robust-adjusted z value	-0.18	0.12	1.26	0.86
Bandwidth	0.60	0.50	0.40	0.62
Effective number of observations	1,309	951	701	1,192
***Panel C**: Price* $> 4.5m$ *RMB*				
RD treatment effect	57.31	32.19	39.28	29.63
Conventional z value	0.63	0.91	0.92	0.90
Robust-adjusted z value	0.72	0.58	0.58	0.91
Bandwidth	0.84	0.73	0.58	0.91
Effective number of observations	2,136	1,628	1,175	2,081
Covariates	NO	YES	YES	YES

Notes: *The sample contains only observations in 2015. The running variable is the distance to the Inner Ring, and a positive distance implies that the block is inside the Inner Ring. In each panel, we report the conventional z value in row 2, followed by the robust-adjusted z value, the optimal bandwidth, and the number of effective observations as Calonico et al. (2014) suggests. Column 1 presents the estimates for a linear model without control variables; and Column 2-4 are for linear, quadratic and cubic polynomial fitting with controls. The optimal bandwidth is selected following Calonico et al. (2014). The bandwidth is in kilometers and the estimated premia are in 10-thousand RMB. * indicates significance at 10%, ** at 5%, and *** at 1%.*

4.3. Placebo test at the Middle Ring

In Shanghai, the Inner Ring is a geographic cutoff used in the criteria for ordinary apartments, while the Middle Ring is not. Thus, the Middle Ring provides another opportunity for a placebo test that mitigates the concern on the social status effect associated with rings. In particular, we perform RD tests at the Middle Ring. As expected, we find no significant price differences in any of the three sub-samples, which helps us exclude the social status effect. The results are presented Table 4, and the plots are in Figure 7. In addition, some may be curious about the premiums in percentage of total price, and we present them in Table 10 for the Inner Ring and Table 11 for the Middle Ring (Appendix A.4).

4.4. Alternative polynomial orders and alternative bandwidths

To check the sensitivity of our results, we perform local linear regressions with varying bandwidths for the group with transaction prices between 3.1 million and 4.5 million RMB. These results are visually presented in Figure 8. We vary the bandwidth from 0.6 km to 2.4 km on each side of the Inner Ring and the Middle Ring, with an increment of 0.2 km each time. The RDrobust package (Calonico et al. (2014)) chooses an optimal bandwidth for the Inner Ring of 0.68 km and 1.44 km for the Middle Ring, respectively. The IK method (Imbens and Kalyanaraman (2012)) suggests

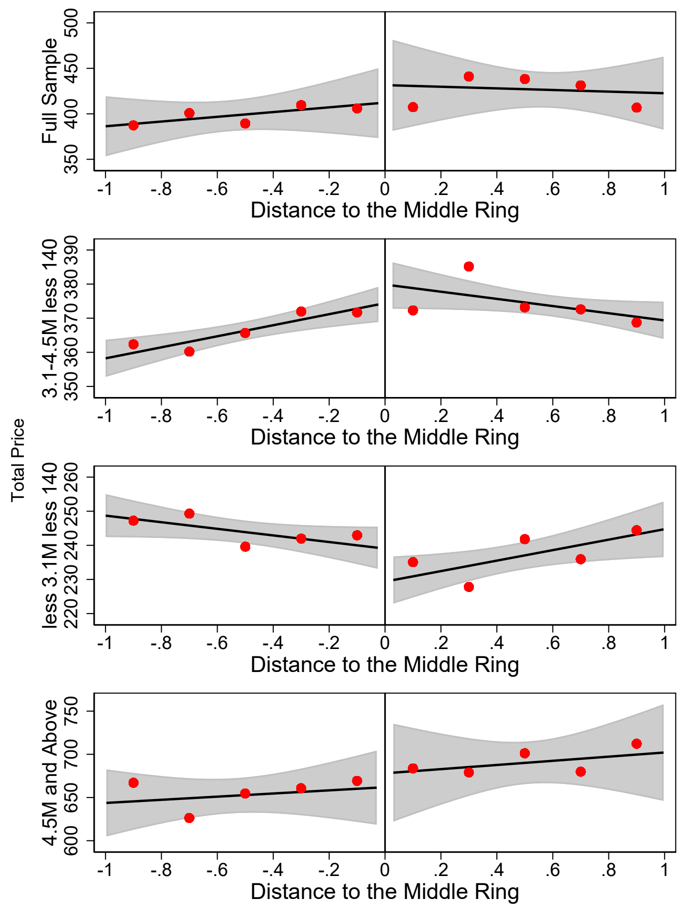

Figure 7: *Regression discontinuity plot at the Middle Ring*

Notes: *Each circle is a binned average of 0.2km. The solid line represents the predicted values of a local linear model estimated using raw data on each side of the Middle Ring, clustered at the residential block level. The shaded area is the 95 percent confidence intervals. The top figure is for the full sample, the second is for those with price between 3.1-4.5 million and size less than 140* m^2, *the third is for those with price less 3.1 million and size less 140* m^2, *the last is for those with price larger than 4.5 million.*

1.59 km for the Inner Ring, and 1.68 km for the Middle Ring, respectively. We also label these two bandwidth choices on Figure 8. For the Inner Ring,

Table 4: *Placebo test: Three price groups at the Middle Ring*

	Linear (1)	Linear (2)	Quadratic (3)	Cubic (4)
***Panel A**: Size* $< 140m^2$; $3.1m \leq$ *Price* $\leq 4.5m$ *RMB*				
RD treatment effect	5.391	8.052	6.130	9.410*
Conventional z value	(1.01)	(1.28)	(0.88)	(1.69)
Robust-adjusted z value	0.64	0.98	0.04	0.47
Bandwidth	1.24	1.49	1.20	1.87
Effective number of observations	5,090	6,122	4,887	7,587
***Panel B**: Size* $< 140m^2$; *Price* $\leq 3.1m$ *RMB*				
RD treatment effect	-8.027	9.207	12.03*	7.337
Conventional z value	-1.56	1.62	1.92	1.44
Robust-adjusted z value	-1.10	1.65	2.14	1.76
Bandwidth	1.53	0.79	0.64	0.99
Effective number of observations	8,669	4,239	3,459	5,352
***Panel C**: Price* $> 4.5m$ *RMB*				
RD treatment effect	3.363	24.05	17.19	27.45
Conventional z value	0.08	0.94	0.61	1.21
Robust-adjusted z value	-0.13	0.58	0.56	0.54
Bandwidth	1.35	1.34	1.07	1.68
Effective number of observations	5,670	5,544	4,515	6,658
Covariates	NO	YES	YES	YES

Notes: *The sample period is Mar, 2016- Dec, 2019. The running variable is the distance to the Middle Ring, and a positive distance implies that the block is inside the Middle Ring. In each panel, we report the conventional z value in row 2, followed by the robust-adjusted z value, the optimal bandwidth, and the number of effective observations as Calonico et al. (2014) suggests. Column 1 presents the estimates for a linear model without control variables; and Column 2-4 are for linear, quadratic and cubic polynomial fitting with controls. The optimal bandwidth is selected following Calonico et al. (2014). The bandwidth is in kilometers and the estimated premia are in 10-thousand RMB. * indicates significance at 10%, ** at 5%, and *** at 1%.*

the estimated price premium from a linear model varies from above 100 thousand RMB to slightly more than 200 thousand RMB with different bandwidth choices. For the Middle Ring, the estimates are insignificant for most of the cases, which is consistent with our expectation.

Then we vary polynomial orders, with bandwidth fixed at 1 km. The estimated price premium of ordinary apartments are robust to polynomial orders varying from one to five. The premium magnitudes vary from around 122 thousand to more than 300 thousand RMB. Therefore, our analysis are robust under various choice of parameters.

5. Discussion

5.1. For younger cohorts

Ordinary apartments are associated with more mortgage credit. Therefore, ordinary apartments should be more attractive to those whose budget are tight. Younger households tend to be more financially constrained. Although we do not have buyer characteristics, we believe that those with stronger demand for high-quality schools are those young couples. Thus, we perform a sub-sample analysis for the apartments in high-quality school districts. We map each block and to its corresponding school manually, and our definition for good schools is based on 2016-2020 Model School List disclosed by Shanghai Municipal Commission of Education. It is worth noting that house quality in good school districts are not necessarily better in other aspects. On the contrary, many of them are small and old, as good primary schools are often located in zones that are developed

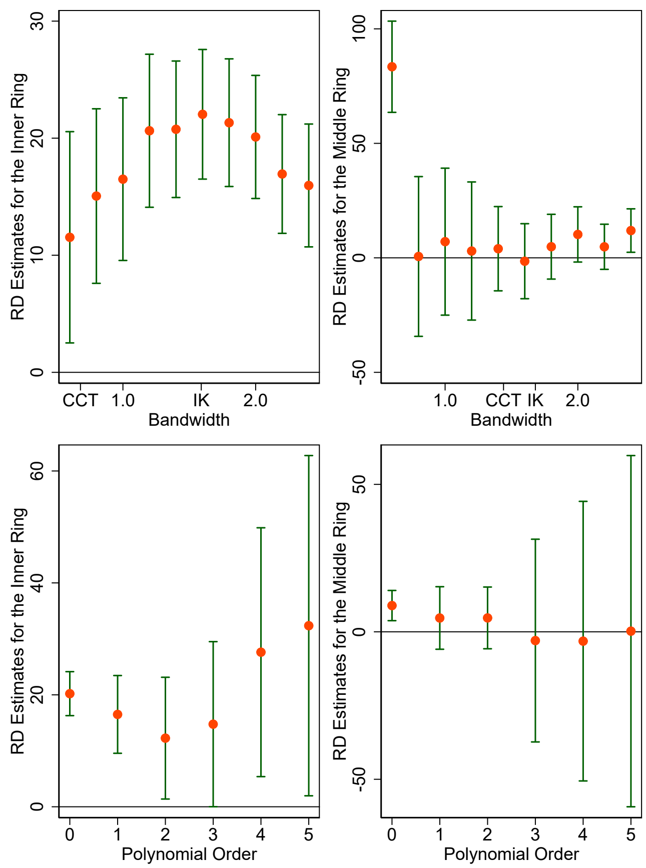

Figure 8: *Sensitivity checks*

Notes: *We check the sensitivity of our estimates for the 3.1-to-4.5-million-RMB group. The premia are in 10-thousand RMB. The top row presents results with different polynomial orders fixing the bandwidth at 1km, and the bottom row presents results of linear model with different bandwidths. We label the optimal bandwidth selected following Calonico et al. (2014) (CCT) and Imbens and Kalyanaraman (2012) (IK) method on the x axis. The left column is for the Inner Ring, while the right column is for the Middle Ring.*

earlier. Many young couples are willing to sacrifice living standards for better education resources for kids.

Consistent with our expectation, the premium for ordinary apartment is larger for the subgroup of houses in high-quality school districts. Table 5 presents the result. The price premium of ordinary apartments over above-ordinary apartments is 146.0 thousand RMB, which is larger than previous estimate 138.8 thousand RMB.

5.2. Donut hole results

Although we have formally shown that there is no evidence suggesting excessive bunching at 4.5 million, the possible bunching behavior near the 4.5 million price cutoff may be still a concern for some readers. We perform a donut hole analysis as a robustness check.[12] Bunching happens if sellers strategically set the prices below 4.5 million to attract more buyers, even if they think the true value for their apartments are above 4.5 million. If that is the case, the seller's optimal strategy should be setting a price slightly below 4.5 million. Therefore, we cut the sample at 4.48 million instead. The estimate of the price premium over the 3.1-4.48 million sample is now 162.6 thousand RMB. Please see Table 6 for more details.

[12] A donut hole analysis is a standard technique that deals with problems near the boundary. For instance, Han et al. (2022) perform a donut hole analysis on the effect of transaction taxes on housing market in the great Toronto area.

Table 5: *Good school districts: Three price groups at the Inner Ring*

	Linear (1)	Linear (2)	Quadratic (3)	Cubic (4)
***Panel A**: Size* $< 140m^2$*;* $3.1m \leq$ *Price* $\leq 4.5m$ *RMB*				
RD treatment effect	15.52**	14.60**	14.66*	17.00***
Conventional z value	2.35	2.05	1.86	2.66
Robust-adjusted z value	1.92	1.32	0.81	1.14
Bandwidth	1.22	0.70	0.56	0.88
Effective number of observations	2,043	1,170	981	1,443
***Panel B**: Size* $< 140m^2$*; Price* $\leq 3.1m$ *RMB*				
RD treatment effect	16.79	0.905	-1.521	2.329
Conventional z value	0.82	0.06	-0.09	0.16
Robust-adjusted z value	0.63	-0.24	0.60	-0.27
Bandwidth	1.21	0.91	0.73	1.14
Effective number of observations	4,029	2,918	2,152	3,560
***Panel C**: Price* $> 4.5m$ *RMB*				
RD treatment effect	-178.7	-60.51	-53.98	-64.36
Conventional z value	-1.62	-1.26	-1.03	-1.40
Robust-adjusted z value	-1.08	-0.80	1.00	-0.61
Bandwidth	0.86	0.83	0.66	1.04
Effective number of observations	2,816	2,674	1,992	3,138
Covariates	NO	YES	YES	YES

Notes: *The sample period is Mar, 2016- Dec, 2019, and we restrict the sample to apartments matched to a high-quality school. The running variable is the distance to the Inner Ring, and a positive distance implies that the block is inside the Inner Ring. In each panel, we report the conventional z value in row 2, followed by the robust-adjusted z value, the optimal bandwidth, and the number of effective observations as Calonico et al. (2014) suggests. Column 1 presents the estimates for a linear model without control variables; and Column 2-4 are for linear, quadratic and cubic polynomial fitting with controls. The optimal bandwidth is selected following Calonico et al. (2014). The bandwidth is in kilometers and the estimated premia are in 10-thousand RMB. * indicates significance at 10%, ** at 5%, and *** at 1%.*

Table 6: *Donut hole estimation at the Inner Ring*

	Linear (1)	Linear (2)	Quadratic (3)	Cubic (4)
Panel A*: Size* $< 140m^2$*;* $3.1m \leq$ *Price* $\leq 4.48m$ *RMB*				
RD treatment effect	12.36**	16.26**	18.72***	16.38***
Conventional z value	2.24	2.44	2.60	2.78
Robust-adjusted z value	1.72	1.72	2.29	2.16
Bandwidth	1.02	0.75	0.60	0.93
Effective number of observations	3,764	2,497	2,113	3,176
Panel B*: Size* $< 140m^2$*; Price* $\leq 3.1m$ *RMB*				
RD treatment effect	17.43	7.113	9.774	7.695
Conventional z value	1.56	0.77	0.99	0.90
Robust-adjusted z value	1.38	0.41	2.14	0.87
Bandwidth	1.02	0.68	0.54	0.85
Effective number of observations	7,309	4,654	3,823	5,750
Panel C*: Price* $> 4.48m$ *RMB*				
RD treatment effect	-98.52	-41.66	-46.66	-37.21
Conventional z value	-1.32	-1.20	-1.16	-1.15
Robust-adjusted z value	-0.88	-1.06	-1.43	-1.14
Bandwidth	0.92	0.80	0.64	1.00
Effective number of observations	5,699	4,739	3,599	5,865
Covariates	NO	YES	YES	YES

Notes: *We lower the price cutoff from exactly 4.5 million to 4.48 million. The sample period is Mar, 2016- Dec, 2019. The running variable is the distance to the Inner Ring, and a positive distance implies that the block is inside the Inner Ring. In each panel, we report the conventional z value row 2, followed by the robust-adjusted z value, the optimal bandwidth, and the number of effective observations as Calonico et al. (2014) suggests. Column 1 presents the estimates for a linear model without control variables; and Column 2-4 are for linear, quadratic and cubic polynomial fitting with controls. The optimal bandwidth is selected following Calonico et al. (2014). The bandwidth is in kilometers and the estimated premia are in 10-thousand RMB. * indicates significance at 10%, ** at 5%, and *** at 1%.*

5.3. Listing price and open house visits

Our previous analysis shows that there is a positive premium for ordinary apartments that are entitled with a lower required down payment ratio. However, the price we observe are outcomes of the bargaining process between sellers and buyers. Therefore, we want to further understand the source of the premium. We want to know whether (1) the sellers are strategically taking advantage of the credit policy by listing their apartments at higher prices; (2) there are more potential buyers for ordinary apartments.

Our data set contains two additional variables, the listing price and the number of open house visit, that might help us test these two conjectures. We perform the same RD estimation for these two variables and find: (1) there is a statistically significant 163.2-thousand-RMB premium in the listing price for the ordinary apartments; (2) there are no significantly more open house visits for ordinary apartments. The listing price should be a good proxy for the seller's target price because the sellers submit it to the dealer before they bargain with any potential buyers. Therefore, the RD estimate on listing prices shows that conditional on apartment characteristics, the sellers seem to take advantage of the favorable position of ordinary apartments in the credit policy. We find no significant open house visits for ordinary apartments. Given the popularity of virtual open house visit on the Lianjia online platform, the actual onsite open house visit may be a noisy measure for the number of potential buyers.

Besides, it is also possible that buyers find the ordinary apartments not more attractive to above-ordinary apartments after taking into account the price premium of ordinary apartments. For details, please see Table 7 and 8.

5.4. A different model specification

We employ a slightly different strategy estimating the RD treatment effect to allow for administrative district fixed effects and year-month fixed effects:

$$y_{ijt} = \beta_0 + \beta_j + \beta_t + \tau m_i + \beta f(x_i) + \gamma m_i f(x_i) + \Gamma' Z_{ijt} + \epsilon_{ijt}, \quad \forall x_i \in (-h, h), \tag{4}$$

of which β_j captures the administrative district fixed effects, and β_t capture the year-month fixed effects.[13] We get a price premium of 140.1 thousand (t-value is 2.45) for the 3.1-4.5 million group, which is pretty similar to the main regression. We then perform the same estimation year by year. As shown in Figure 9, the premium has a larger magnitude and is more significant for the years 2016-2019 than for 2015. It is especially large in 2018 and 2019, when the housing market is relatively stable.

[13] The Inner Ring goes through 6 administrative districts: Pudong, Jing'an, Xuhui, Changning, Hongkou, and Yangpu.

Table 7: *Listing Price: Three price groups at the Inner Ring*

	Linear (1)	Linear (2)	Quadratic (3)	Cubic (4)
***Panel A**: Size* $< 140m^2$*;* $3.1m \leq$ *Price* $\leq 4.5m$ *RMB*				
RD treatment effect	14.84**	16.93**	21.52***	16.59**
Conventional z value	2.41	2.18	2.67	2.36
Robust-adjusted z value	1.92	1.65	3.43	2.46
Bandwidth	0.85	0.75	0.60	0.93
Effective number of observations	2,041	1,653	1,415	2,107
***Panel B**: Size* $< 140m^2$*; Price* $\leq 3.1m$ *RMB*				
RD treatment effect	19.64*	8.114	12.18	8.527
Conventional z value	1.71	0.81	1.16	0.92
Robust-adjusted z value	1.52	0.47	3.53	1.10
Bandwidth	1.07	0.69	0.55	0.86
Effective number of observations	4,928	3,062	2,492	3,905
***Panel C**: Price* $> 4.5m$ *RMB*				
RD treatment effect	-128.5*	-51.33	-57.78	-47.02
Conventional z value	-1.83	-1.47	-1.54	-1.42
Robust-adjusted z value	-1.43	-1.60	-1.43	-1.42
Bandwidth	1.13	1.04	0.83	1.30
Effective number of observations	3,860	3,398	2,775	4,127
Covariates	NO	YES	YES	YES

Notes: *The dependent variable is the listing price. The sample period is Mar, 2016- Dec, 2019. The running variable is the distance to the Inner Ring, and a positive distance implies that the block is inside the Inner Ring. In each panel, we report the conventional z value in row 2, followed by the robust-adjusted z value, the optimal bandwidth, and the number of effective observations as Calonico et al. (2014) suggests. Column 1 presents the estimates for a linear model without control variables; and Column 2-4 are for linear, quadratic and cubic polynomial fitting with controls. The optimal bandwidth is selected following Calonico et al. (2014). The bandwidth is in kilometers and the estimated premia are in 10-thousand RMB. * indicates significance at 10%, ** at 5%, and *** at 1%.*

Table 8: *Number of open house visits at the Inner Ring*

	Linear (1)	Linear (2)	Quadratic (3)	Cubic (4)
***Panel A**: Size* $< 140m^2$*;* $3.1m \leq$ *Price* $\leq 4.5m$ *RMB*				
RD treatment effect	5.084	4.529	3.456	5.320*
Conventional z value	1.54	1.30	0.87	1.69
Robust-adjusted z value	0.88	0.58	0.16	0.35
Bandwidth	0.69	0.65	0.52	0.81
Effective number of observations	1,424	1,240	991	1,482
***Panel B**: Size* $< 140m^2$*; Price* $\leq 3.1m$ *RMB*				
RD treatment effect	4.876**	1.944	2.787	1.927
Conventional z value	1.97	0.88	1.15	0.98
Robust-adjusted z value	1.54	0.58	0.71	0.95
Bandwidth	0.94	0.77	0.62	0.96
Effective number of observations	3,671	2,740	2,323	3,650
***Panel C**: Price* $> 4.5m$ *RMB*				
RD treatment effect	0.359	3.082	3.554	2.293
Conventional z value	0.09	0.83	0.87	0.68
Robust-adjusted z value	0.24	0.75	0.28	0.86
Bandwidth	1.02	1.05	0.84	1.31
Effective number of observations	2,979	2,825	2,300	3,410
Covariates	NO	YES	YES	YES

Notes: *The dependent variable is numbers of open house visits. The sample period is Mar, 2016- Dec, 2019. The running variable is the distance to the Inner Ring, and a positive distance implies that the block is inside the Inner Ring. In each panel, we report the conventional z value in row 2, followed by the robust-adjusted z value, the optimal bandwidth, and the number of effective observations as Calonico et al. (2014) suggests. Column 1 presents the estimates for a linear model without control variables; and Column 2-4 are for linear, quadratic and cubic polynomial fitting with controls. The optimal bandwidth is selected following Calonico et al. (2014). The bandwidth is in kilometers and the estimated premia are in 10-thousand RMB. * indicates significance at 10%, ** at 5%, and *** at 1%.*

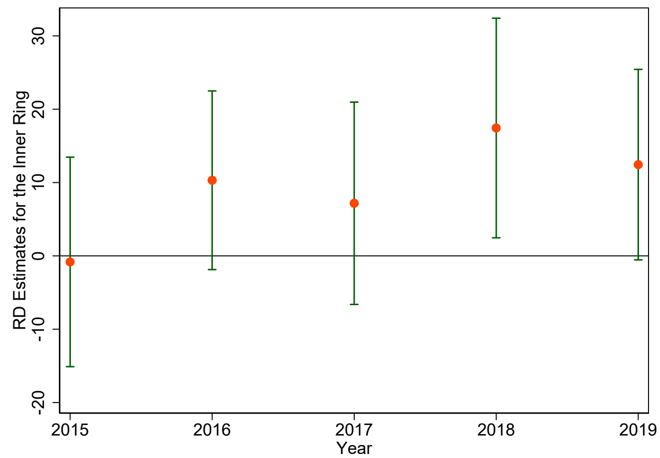

Figure 9: *Estimated price premium across years*

Notes: *This figure shows the dynamics of the estimated premium for the 3.1-to-4.5-million-RMB group at the Inner Ring across years. We perform year-by-year regressions as in* $y_{ijt} = \beta_0 + \beta_j + \beta_t + \tau m_i + \beta f(x_i) + \gamma m_i f(x_i) + \Gamma' Z_{ijt} + \epsilon_{ijt}$ *for observations with* $x_i \in (-h, h)$*, and the bandwidth (h) is fixed at 0.68km as selected following Calonico et al. (2014).*

6. Conclusion

In 2016, the implementation of a differential credit policy in Shanghai gave repeated buyers higher credit availability when buying ordinary apartments than buying above-ordinary apartments. Using this unique setting, we establish a causal relationship between the down payment requirement and housing prices by employing a regression discontinuity design with transaction level data. We find that this differential credit policy favoring the ordinary apartments raises the price of ordinary apartments by around 3.71%. Our paper adds a new piece of causal evidence suggesting that credit supply matters for housing prices. Our paper also shows clearly that the differential credit policy has an important redistribution effect. It creates a price wedge between quite similar apartments and leads to potential welfare loss.

A policy implication of our findings is that a differential credit policy based on geographic boundary may increase wealth inequality. For most households, housing asset is the major household asset, and the differential credit policy in Shanghai actually gives advantages to homeowners inside the Inner Ring relative to those outside the ring. In the pre-policy year 2015, the average house value inside the Inner Ring was already 2.17 million yuan larger than that outside the ring.[14] The differential policy further widens the gap of household housing value on the two sides.

There are several possible extensions stemming from this paper. For instance, with proper data like credit card usage records, we may investigate how the differential credit policy generates heterogeneous effects on household consumption behavior. With information of household characteristics, we may examine how such a policy affects demographic sorting within a city. With detailed information of home mortgage and household asset, we can test how the policy influences household leverage, which has implications for economic volatility.

[14] In 2015, the average total price for apartments within the Inner Ring is 5.52 million, and 3.35 million for those between the Inner Ring and the Outer Ring.

References

Benito, Andrew, "The down-payment constraint and UK housing market: does the theory fit the facts?," *Journal of Housing Economics*, 2006, *15* (1), 1–20.

Calonico, Sebastian, Matias D Cattaneo, and Rocio Titiunik, "Robust nonparametric confidence intervals for regression-discontinuity designs," *Econometrica*, 2014, *82* (6), 2295–2326.

Chen, Kaiji, Qing Wang, Tong Xu, and Tao Zha, "Aggregate and Distributional Impacts of LTV Policy: Evidence from China's Micro Data," November 2020, (28092).

Chetty, Raj, John N Friedman, Tore Olsen, and Luigi Pistaferri, "Adjustment costs, firm responses, and micro vs. macro labor supply elasticities: Evidence from Danish tax records," *The Quarterly Journal of Economics*, 2011, *126* (2), 749–804.

Coffee, Neil T, Tony Lockwood, Peter Rossini, Theo Niyonsenga, and Stanley McGreal, "Composition and context drivers of residential property location value as a socioeconomic status measure," *Environment and Planning B: Urban Analytics and City Science*, 2020, *47* (5), 790–807.

de Neef, H Özlem Dursun, "The transmission of bank liquidity shocks: Evidence from house prices," *Review of Finance*, 2019, *23* (3), 629–658.

Duca, John V, John Muellbauer, and Anthony Murphy, "House prices and credit constraints: Making sense of the US experience," *The Economic Journal*, 2011, *121* (552), 533–551.

Favara, Giovanni and Jean Imbs, "Credit supply and the price of housing," *American Economic Review*, 2015, *105* (3), 958–92.

Favilukis, Jack, Sydney C Ludvigson, and Stijn Van Nieuwerburgh, "The macroeconomic effects of housing wealth, housing finance, and limited risk sharing in general equilibrium," *Journal of Political Economy*, 2017, *125* (1), 140–223.

Gelman, Andrew and Guido Imbens, "Why high-order polynomials should not be used in regression discontinuity designs," *Journal of Business & Economic Statistics*, 2019, *37* (3), 447–456.

Hahn, Jinyong, Petra Todd, and Wilbert Van der Klaauw, "Identification and estimation of treatment effects with a regression-discontinuity design," *Econometrica*, 2001, *69* (1), 201–209.

Han, Lu, Chandler Lutz, Benjamin Sand, and Derek Stacey, "The effects of a targeted financial constraint on the housing market," *Review of Financial Studies*, 2021, *34* (8), 3742–3788.

_, L Rachel Ngai, and Kevin D Sheedy, "To own or to rent? The effects of transaction taxes on housing markets," *Working Paper*, 2022.

Imbens, Guido and Karthik Kalyanaraman, "Optimal bandwidth choice for the regression discontinuity estimator," *The Review of Economic Studies*, 2012, *79* (3), 933–959.

Imbens, Guido W and Thomas Lemieux, "Regression discontinuity designs: A guide to practice," *Journal of econometrics*, 2008, *142* (2), 615–635.

Jordà, Òscar, Moritz Schularick, and Alan M Taylor, "The great mortgaging: housing finance, crises and business cycles," *Economic Policy*, 2016, *31* (85), 107–152.

Kiyotaki, Nobuhiro, Alexander Michaelides, and Kalin Nikolov, "Winners and losers in housing markets," *Journal of Money, Credit and Banking*, 2011, *43* (2-3), 255–296.

Kleven, Henrik J and Mazhar Waseem, "Using notches to uncover optimization frictions and structural elasticities: Theory and evidence from Pakistan," *The Quarterly Journal of Economics*, 2013, *128* (2), 669–723.

Kuttner, Kenneth N and Ilhyock Shim, "Can non-interest rate policies stabilize housing markets? Evidence from a panel of 57 economies," *Journal of Financial Stability*, 2016, *26*, 31–44.

Landvoigt, Tim, Monika Piazzesi, and Martin Schneider, "The housing market (s) of San Diego," *American Economic Review*, 2015, *105* (4), 1371–1407.

Lee, David S and Thomas Lemieux, "Regression discontinuity designs in economics," *Journal of Economic Literature*, 2010, *48* (2), 281–355.

Mian, Atif and Amir Sufi, "The consequences of mortgage credit expansion: Evidence from the US mortgage default crisis," *The Quarterly Journal of Economics*, 2009, *124* (4), 1449–1496.

_ **and** _ , "Credit supply and housing speculation," *The Review of Financial Studies*, 2022, *35* (2), 680–719.

Ortalo-Magne, Francois and Sven Rady, "Housing market dynamics: On the contribution of income shocks and credit constraints," *The Review of Economic Studies*, 2006, *73* (2), 459–485.

Sommer, Kamila, Paul Sullivan, and Randal Verbrugge, "The equilibrium effect of fundamentals on house prices and rents," *Journal of Monetary Economics*, 2013, *60* (7), 854–870.

Stein, Jeremy C, "Prices and trading volume in the housing market: A model with down-payment effects," *The Quarterly Journal of Economics*, 1995, *110* (2), 379–406.

Tzur-Ilan, Nitzan, "Adjusting to Macroprudential Policies: Loan-to-Value Limits and Housing Choice," *The Review of Financial Studies*, 2023, p. hhad035.

Vigdor, Jacob L, "Liquidity constraints and housing prices: Theory and evidence from the VA mortgage program," *Journal of Public Economics*, 2006, *90* (8-9), 1579–1600.

Zevelev, Albert Alex, "Does collateral value affect asset prices? Evidence from a natural experiment in Texas," *The Review of Financial Studies*, 2021, *34* (9), 4373–4411.

Zhou, Zhengyi, "Overreaction to policy changes in the housing market: Evidence from Shanghai," *Regional Science and Urban Economics*, 2016, *58*, 26–41.

A. Appendix

A.1. A simple illustrative framework

Zevelev (2021) provides a simple three-period model, and we build our simple framework based on it. We solve the model and argue that price p_0 increases with κ under some assumption. Setting up the Lagrangian yields

$$\begin{aligned}
\mathcal{L}(c_0, c_1, c_2, h, b, \lambda_0, \lambda_1, \lambda_2, \mu_0) &= u(c_0, h) + \beta \cdot u(c_1, h) + \beta^2 \cdot c_2 \\
&- \lambda_0 \cdot (c_0 + p_0 \cdot h - y_0 - b) \\
&- \lambda_1 \cdot (c_1 + r_0 \cdot b - y_1) \\
&- \lambda_2 \cdot (c_2 + b - y_2 - p_2 \cdot h) \\
&- \mu_0 \cdot (b - \kappa \cdot p_0 \cdot h)
\end{aligned}$$

The FOC with respect to h and b yields equation

$$p_0 = \frac{1}{\lambda_0} \left((1 + \beta) \cdot u_h + \mu_0 \cdot \kappa \cdot p_0 + \lambda_2 \cdot p_2 \right)$$

and

$$\mu_0 = \lambda_0 - r_0 \cdot \lambda_1 - \lambda_2,$$

respectively. Solving for price p_0, we have

$$p_0 = \frac{(1 + \beta) \cdot u_h + \lambda_2 \cdot p_2}{\lambda_0 - \mu_0 \cdot \kappa}. \tag{5}$$

To argue that price is increasing function of κ, we need to differentiate p_0 with respect to κ. Here we make a few simplifying assumptions. First, we assume that the marginal utility u_h is relatively flat in h so that $\partial u_h / \partial \kappa \approx 0$. Therefore, the numerator of equation (5) is approximately a constant as $\lambda_2 = \beta^2$. Now we differentiate the denominator ($D \equiv \lambda_0 - \mu_0 \cdot \kappa$) with respect to κ:

$$\frac{\partial D}{\partial \kappa} = \frac{\partial \lambda_0}{\partial \kappa} - \kappa \cdot \left(\frac{\partial \lambda_0}{\partial \kappa} - r_0 \cdot \frac{\partial \lambda_1}{\partial \kappa} \right) - \mu_0 \approx \frac{\partial \lambda_0}{\partial \kappa} \cdot (1 - \kappa) - \mu_0 \leq 0.$$ [15]

While λ_0 is the marginal utility of consumption at $t = 0$, we argue that $\partial\lambda_0/\lambda\kappa \leq 0$ for the following reasons: (1) relaxing the borrowing constraint is equivalent to relaxing the budget constraint in period 0; (2) marginal utility of consumption (λ_0) decreases with consumption. Therefore, we show that apartment prices increase with credit availability, provided with the assumptions above.

A.2. Bunching response?

The key comparison of our estimate is between the apartments within the Inner Ring and those apartments of similar quality but outside the Inner Ring. For those apartments in the Inner Ring, potential bunching around 4.5 million would lead to underpricing of some higher-quality apartments. And this would bias our estimate. For example, without the differential credit policy, an apartment sells at 4.54 million. With the implementation of the differential credit policy, the owner may sell this apartment at 4.49 million (a price that helps the apartment to be classified as an ordinary apartment) in order to attract more potential buyers.

We argue why this is not the case in our setting and provide a formal

[15] Because $\partial\lambda_0/\partial\kappa$ and $\partial\lambda_1/\partial\kappa$ are of the same magnitude and the mortgage rate is relatively small, we can ignore the second term in the bracket.

test for it. The key lies in the fact that, within the Chinese context, the price reported to the government and banks may be different from the actual transaction price. It is possible that sellers and buyers collude and under-report the price to the government and the bank for more credit. For example, both parties agree to report to the government that the transaction price is 4.5 million, but the apartment actually sells at 4.6 million. Thus, the buyer can get a 2.25 million credit if the reported price is 4.5 million. She can only get a 1.38 million credit if she tells the government and the bank the true transaction price.

Reporting a different contract to the government and the bank is a familiar phenomenon in China, which is sometimes referred as the dual contracts.[16] Anecdotal evidence suggests that employees from the bank knows it, and so does the government officers. The situation is unlike the one in some other countries where the housing transactions involve buyers, sellers, brokers, and lawyers. Dual contracts can lead to severe punishments in such countries, possibly disbarment of lawyers, which makes a dual contract situation almost impossible. In China, the bargaining process only involves the buyer and the seller, with the broker trying to persuade both parties to get the deal done.

If we were to analyze ***the reported price*** to the government, we would expect a large bunching around the price cutoff in the Inner Ring at

[16] There are two contracts with the fake one reported to the authority and the real one is privately known by the sellers and buyers.

4.5 million. However, there should be no bunching around ***the actual transaction price*** (our data) cutoff if everyone can report a different price when necessary to get more credit. We formally show that no detectable bunching behavior by performing the bunching estimation as in Chetty et al. (2011). We also allow for bias toward certain integers following Kleven and Waseem (2013). We find no evidence for significant bunching around 4.5 million as we estimate a $\hat{b}$ of 0.76 with a standard deviation of 2.88.

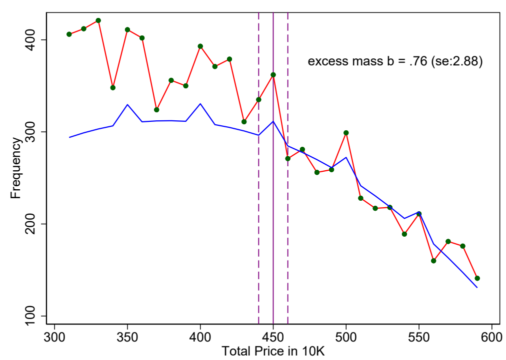

Figure 10: *Bunching estimation around 4.5 million inside the Inner Ring*

Notes: *The red line is the connected transaction data. Each dot is the number of transactions binned in 100,000 RMB. The blue line is the counterfactual fitted line, and we allow for the multiples of 500,000 RMB to have a larger transaction volume due to the fact that people may have a bias toward these numbers. The standard error is in the parentheses, and we get the standard error by bootstrapping.*

The key idea of bunching estimation is to compare the actual distribution of transactions across different prices with a counterfactual density–what the distribution would look like if there were no change in the required down payment ratio at the price cutoff. Following the literature, we first group the data into bins of transaction price, and then we count the number of transactions in each bin. After that we fit a polynomial to the counts of transactions in each bin by estimating:

$$C_j = \sum_{i=0}^{q} \beta_i (Z_j)^i + \sum_{i=-R}^{R} \gamma_i \cdot \mathbb{1}\left\{Z_j = i\right\} + \sum_{r \in I} \rho \cdot \mathbb{1}\left\{{}^{Z_j}/_{r} \in N\right\} + \epsilon_i,$$

where C_j is the number of transactions in price bin j, the width for each bin is 100 thousand (0.1 million). Z_j is the price relative to the cutoff price 4.5 million in 100 thousand RMB. For example, $Z_j = 1$ if the price bin is 4.5-4.6 million. q is the order of the polynomial. If bunching happens in a certain region, we allow for a dummy variable for each bin in the region so that we are not fitting the polynomial in this region. In our case, bunching may happen between 4.4-4.6 million, so we include two dummies for the 4.4-4.5 million bin and the 4.5-4.6 million bin. Since the bin width is 0.1 million each, $R = 1$. Following the literature allowing for bias toward certain integer numbers, we also include dummy variable for bins contains these integer number. We choose $r = 0.5$ million, which suggests psychological bias toward numbers of 3.5 million, 4 million, 4.5 million, etc.

The estimation of the counterfactual distribution is the predicted values from the above regression by setting all the dummies in the excluded region to zero, but not omitting the contribution of the round-number dummies:

$$\hat{C}_j^0 = \sum_{i=0}^{q} \hat{\beta}_i (Z_j)^i + \sum_{r \in I} \hat{\rho} \cdot \mathbb{1}\left\{{}^{Z_j}/_{r} \in N\right\}.$$

The estimate of excess bunching is defined as the difference between the actual numbers of transactions in each price bins minus the predicted numbers within the excluded range:

$$\hat{B}^0 = \sum_{-R}^{R} (C_j - \hat{C}_j^0).$$

Then the empirical estimate of b is determined as follows:

$$\hat{b} = \frac{\hat{B}^0}{\sum_{j=-R}^{R} \hat{C}_j / N_j},$$

where N_j is the number of bins in the excluded region. The estimator equals the fraction of excess bunching relative to the predicted average observations in each bin in the excluded region. Following the literature, we bootstrap the standard error for the estimation. And the result is presented in Figure 10.

A.3. Adjusted-sample results

Without the differential credit policy, Apartment C inside the Inner Ring and Apartment D outside the Inner Ring, which have similar quality, sell at the same price of 4.5 million. Under the differential credit policy, Apartment C sells at a price higher than 4.5 million since repeated buyers can get more credit for buying Apartment C. While we brutally set the price range as 3.1 million to 4.5 million for Panel A for those apartments both inside and outside the Inner Ring, we are actually dropping Apartment C, whose quality are similar to Apartment D, from Panel A. This can potentially lead to a downward bias in our price premium estimates as we are dropping the top quality apartments inside the Inner Ring.

One simple way to relieve the above concern is to redo the exercises setting the price range as 3.1m to 4.5m plus the price premium for those inside the Inner Ring and still 3.1m to 4.5m for those outside the Inner Ring. The estimated price premium is higher than previously estimated as in Table 9. All the covariates are balanced as in Figure 11.

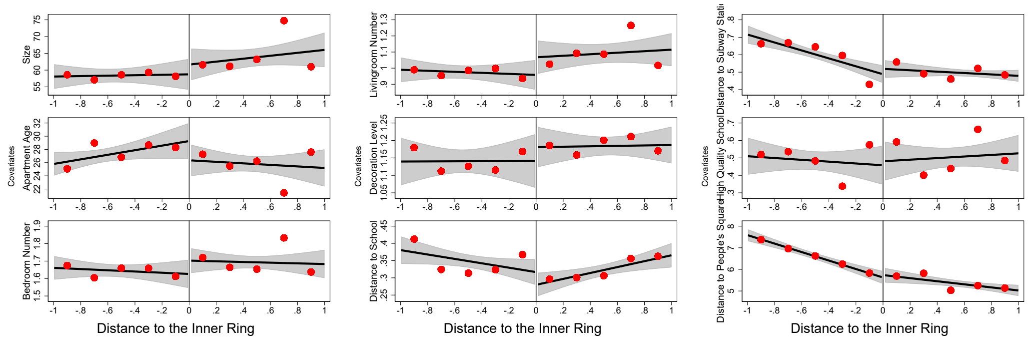

Figure 11: *Adjusted balanced covariates checks*

Notes: *After knowing that those apartments within the Inner Ring is sold with a price premium, we adjusted the sample by setting the price range as 3.1m to 4.5m plus the price premium for those inside the Inner Ring and still 3.1m to 4.5m for those outside the Inner Ring. All the covaraites are balanced with an improvement on the variable size.*

Table 9: *Adjusted-sample results: Three price groups at the Inner Ring*

	Linear	Linear	Quadratic	Cubic
***Panel A**: Size* $< 140m^2$; $3.1 - 4.64m$ *RMB inside,* $3.1 - 4.5m$ *RMB outside*				
RD treatment effect	17.33***	20.35***	24.15***	20.20***
Conventional z value	2.94	2.83	3.12	3.14
Robust-adjusted z value	2.31	2.07	2.88	2.64
Bandwidth	0.97	0.73	0.58	0.91
Effective number of observations	3,964	2,719	2,292	3,446
***Panel B**: Size* $< 140m^2$; *Price* $\leq 3.1m$ *RMB*				
RD treatment effect	14.85	3.707	5.979	4.580
Conventional z value	1.33	0.39	0.60	0.52
Robust-adjusted z value	1.09	0.11	1.86	0.51
Bandwidth	1.02	0.68	0.54	0.85
Effective number of observations	7,386	4,727	3,872	5,815
***Panel C**: Price* $> 4.64m$ *RMB inside, Price* $> 4.5m$ *RMB outside*				
RD treatment effect	-78.44	-40.13	-46.35	-34.96
Conventional z value	-1.07	-1.15	-1.15	-1.07
Robust-adjusted z value	-0.76	-1.09	-1.37	-1.15
Bandwidth	0.96	0.82	0.65	1.02
Effective number of observations	5,748	4,604	3,549	5,679
Covariates	NO	YES	YES	YES

Notes: *We cut our sub-samples slightly differently. In Panel A, we compare those apartments with price between 3.1-4.64 million inside the Inner Ring with those apartments with price between 3.1-4.5 million outside the Inner Ring. In Panel C, we compare apartments with price larger than 4.64 million inside the Inner Ring with those apartments with price larger than 4.5 million outside the Inner Ring. The sample period is Mar, 2016- Dec, 2019. The running variable is the distance to the Inner Ring, and a positive distance implies that the block is inside the Inner Ring. In each panel, we report the conventional z value in row 2, followed by the robust-adjusted z value, the optimal bandwidth, and the number of effective observations as Calonico et al. (2014) suggests. Column 1 presents the estimates for a linear model without control variables; and Column 2-4 are for linear, quadratic and cubic polynomial fitting with controls. The optimal bandwidth is selected following Calonico et al. (2014). The bandwidth is in kilometers and the estimated premia are in 10-thousand RMB. * indicates significance at 10%, ** at 5%, and *** at 1%.*

A.4. Premium in percentage

Table 10: *Main results (in percentage): Three price groups at the Inner Ring*

	Linear	Linear	Quadratic	Cubic
***Panel A**: Size* $< 140m^2$; $3.1m \leq$ *Price* $\leq 4.5m$ *RMB*				
RD treatment effect	3.210**	3.751**	4.596***	3.959***
Conventional z value	2.31	2.55	2.87	2.96
Robust-adjusted z value	1.72	1.68	2.11	2.12
Bandwidth	0.81	0.68	0.55	0.85
Effective number of observations	3,005	2,441	1,988	3,022
***Panel B**: Size* $< 140m^2$; *Price* $\leq 3.1m$ *RMB*				
RD treatment effect	7.143	1.745	2.706	2.107
Conventional z value	1.24	0.37	0.55	0.48
Robust-adjusted z value	0.96	0.11	1.75	0.52
Bandwidth	1.01	0.68	0.54	0.85
Effective number of observations	7,378	4,732	3,872	5,887
***Panel C**: Price* $> 4.5m$ *RMB*				
RD treatment effect	-15.04*	-7.051	-7.228	-6.402
Conventional z value	-1.73	-1.22	-0.99	-1.33
Robust-adjusted z value	-1.33	-1.15	-0.78	-0.82
Bandwidth	0.85	0.74	0.59	0.93
Effective number of observations	5,319	4,296	3,332	5,320
Covariates	NO	YES	YES	YES

Notes: *The sample period is Mar, 2016- Dec, 2019. The running variable is the distance to the Inner Ring, and a positive distance implies that the block is inside the Inner Ring. In each panel, we report the conventional z value in row 2, followed by the robust-adjusted z value, the optimal bandwidth, and the number of effective observations as Calonico et al. (2014) suggests. Column 1 presents the estimates for a linear model without control variables; and Column 2-4 are for linear, quadratic and cubic polynomial fitting with controls. The optimal bandwidth is selected following Calonico et al. (2014). The bandwidth is in kilometers and the estimated premia are in 10-thousand RMB. * indicates significance at 10%, ** at 5%, and *** at 1%.*

Table 11: *Placebo test (in percentage): Three price groups at the Middle Ring*

	Linear	Linear	Quadratic	Cubic
***Panel A**: Size* $< 140m^2$*;* $3.1m \leq$ *Price* $\leq 4.5m$ *RMB*				
RD treatment effect	1.450	2.157	1.659	2.523*
Conventional z value	1.02	1.27	0.88	1.68
Robust-adjusted z value	0.65	0.97	0.06	0.47
Bandwidth	1.24	1.49	1.19	1.87
Effective number of observations	5,090	6,101	4,885	7,587
***Panel B**: Size* $< 140m^2$*; Price* $\leq 3.1m$ *RMB*				
RD treatment effect	-3.421	3.908	5.191*	3.011
Conventional z value	-1.36	1.54	1.85	1.32
Robust-adjusted z value	-0.90	1.56	2.17	1.75
Bandwidth	1.24	0.79	0.63	0.99
Effective number of observations	6,838	4,238	3,404	5,320
***Panel C**: Price* $> 4.5m$ *RMB*				
RD treatment effect	4.328	7.525*	6.931	7.866**
Conventional z value	0.70	1.85	1.52	2.20
Robust-adjusted z value	0.49	1.37	1.01	1.29
Bandwidth	1.35	1.37	1.10	1.72
Effective number of observations	5,711	5,728	4,665	6,778
Covariates	NO	YES	YES	YES

Notes: *The sample period is Mar, 2016- Dec, 2019. The running variable is the distance to the Middle Ring, and a positive distance implies that the block is inside the Middle Ring. In each panel, we report the conventional z value in row 2, followed by the robust-adjusted z value, the optimal bandwidth, and the number of effective observations as Calonico et al. (2014) suggests. Column 1 presents the estimates for a linear model without control variables; and Column 2-4 are for linear, quadratic and cubic polynomial fitting with controls. The optimal bandwidth is selected following Calonico et al. (2014). The bandwidth is in kilometers and the estimated premia are in 10-thousand RMB. * indicates significance at 10%, ** at 5%, and *** at 1%.*