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Research Paper

Windfall gains and household consumption: Regression-discontinuity evidence from urban China's preferential housing policies

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A B S T R A C T

This paper identifies the effect of windfall gains in housing wealth on household consumption in China, exploiting a "jump" in housing wealth generated by *unexpected* changes in urban China's commercial housing policy in 2006–2010 that lowered the down payment ratio and property deed tax rate for units under or equal to 90 m^2 in size. A sharp regression discontinuity design applied to the China Family Panel Studies data reveals a substantial housing-wealth effect. Specifically, households with units just below 90 m^2 spent 26.6 % more on household consumption (including clothing, daily expenses, transportation and communication, as well as education and entertainment expenditures) relative to their counterparts with units just above 90 m^2. The effects of housing policies on household consumption persisted with prolonged policy exposure and were more pronounced in locations with greater policy-induced disparities in housing price and housing value growth rates on either side of the 90-m^2 cutoff. The housing-wealth effect is also greater among older homeowners, multi-unit households, and households with savings, suggesting that the anticipation of higher future housing wealth and a reduced saving motive (rather than a collateral effect) work as driving channels.

1. Introduction

The development of China's housing market in the early 2000s was accompanied by rapid urbanization and a massive influx of rural labor into its cities, numbering in the millions (An et al., 2024; Meng, 2012). The surge in urban population created an unprecedented demand for residential housing, substantially escalating housing prices in urban China. Official statistics indicate that the average annual growth rate of housing prices in 35 major Chinese cities stood at 12.68 % in the 2000s (National Bureau of Statistics of China (NBSC), 2011). The soaring housing prices greatly elevated housing-price-to-income ratios, imposing a heavy burden on low- and middle-income homebuyers, which might have suppressed their household consumption and undermined their overall well-being (Fang et al., 2015). These challenges prompted scholars to express concerns regarding potential risks within China's housing market;

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some even warned about the possible emergence of a housing bubble (Glaeser et al., 2017; Wu et al., 2016).

In reaction, the Chinese government launched a series of regulatory policies in the mid-2000s to stabilize housing prices in urban China so that the robust housing demand of low- to middle-income residents could be met (Yang and Chen, 2014). In May 2006, the State Council and nine ministries of China jointly issued a housing policy known as "*National Article Six*," reducing the down payment ratio of personal housing mortgage loans from 30 % to 20 % for units with size under or equal to 90 m^2, while keeping that for units above 90 m^2 unchanged at 30 % (General Office of the State Council, PRC, 2006).[1] In October 2008, the central government lowered the property deed tax rate from 3 % to 1 % for first-time purchased units with an area of 90 m^2 or less. The discontinuity in the property deed tax rate at 90 m^2 was further consolidated in another directive jointly issued by the Ministry of Finance, the State Administration of Taxation, and the Ministry of Housing and Urban-Rural Development in September 2010.

These directives initiated preferential housing policies based on the size of the purchased housing units, providing a valuable opportunity to test whether *unexpected* housing value (*perceived* housing wealth) gains resulting from changes in housing prices can boost household consumption for homeowners. In particular, these policies introduced a discontinuity structure in the down payment ratio and property deed tax rate at the 90-m^2 cutoff, triggering housing price and wealth growth at varying rates for units on either side of the cutoff. To the extent that households with units just below and above the 90-m^2 cutoff are otherwise comparable, the policy-induced jumps in housing-wealth growth rates at the cutoff facilitate the identification of housing-wealth effects.

To better understand how these housing policies impacted housing prices and household consumption, we first derive the housing market clearing condition to demonstrate how changes in the down payment ratio and deed tax influence the equilibrium housing price. We then constructed a two-period household consumption model, in which homeowners smooth their consumption by reallocating the total exogenous lifetime income and anticipated future housing wealth between the two periods. A comparative statics analysis unveils that a reduction in either the down payment ratio or the deed tax raises the equilibrium housing price, thereby increasing long-term housing wealth. This housing-wealth effect, in turn, stimulates current consumption among homeowners with units under or equal to 90 m^2.

Based on these theoretical insights, we apply a sharp regression discontinuity (RD) design to gauge the effect of *unexpected* housing-value growth on urban Chinese households' consumption expenditure, using data on 7655 households drawn from five waves of the China Family Panel Studies (CFPS), a nearly nationally representative survey covering 25 province-level regions in China. Specifically, focusing on households that purchased independent-property units before policy enactment in 2006, our sharp-RD estimates suggest that, as a result of the preferential housing policies, households with units just below 90 m^2 enjoyed a faster housing-price growth rate than those with units just above 90 m^2, which translated into a greater increase in housing wealth for the former. Correspondingly, the former households spent nearly 27 % more on consumption than the latter. The consumption-stimulating effect of preferential housing policies also persisted with prolonged policy exposure. The estimated effects of preferential housing policies on consumption remain robust across a wide range of checks: we considered the influence of supply-side policies around the cutoff, ruled out confounding effects of household net income, experimented with alternative bandwidths and bandwidth selection methods, kernel functions and polynomial orders, imposed placebo policy cutoffs, addressed possible treatment misassignments, and performed parametric RD estimations.

Informative heterogeneity patterns in housing-wealth effects are also discovered. Whereas the policy-induced housing-wealth growth exerted significantly positive consumption responses among near-retirement and retired households, the effects are statistically insignificant for younger households. Consumption responses were also stronger among households with multiple units than among those with single units. Moreover, consumption responses were limited to households with savings and were particularly pronounced among those residing in regions with higher sex ratios at birth and at marriage. These results imply that the housing-wealth effect on consumption we found is predominantly driven by an *unexpected* wealth effect and a reduced savings motive—both precautionary and competitive—rather than a collateral effect.

Our study contributes to the literature in two ways. First, it advances knowledge of the causal effects of housing policies on housing wealth. Due to recurring identification challenges arising from unobservable confounders and households' self-selection into different housing sizes and locations (Ioannides and Ngai, 2025), only a limited number of studies have successfully inferred causality from housing wealth on household outcomes (Aladangady, 2017; Muellbauer, 2008). In the context of China, several studies have implemented RD designs facilitated by *National Article Six* and subsequent policies to examine the effects of housing wealth on household outcomes.[2] For instance, Li et al. (2020) found that housing wealth generated by these policies deterred labor supply. More recently, Li et al. (2023) discovered significantly negative effects of housing wealth on children's cognitive and noncognitive skills. Our study adds to this emerging literature from the perspective of household consumption, helping to depict a fuller picture of the impact of preferential housing policies in and beyond China.[3]

Second, this study addresses the crucial question of the significance of the housing-wealth effect in a developing-country setting. To our knowledge, research on the "housing wealth–household consumption" relationship has been sparse in developing countries (Wang

[1] This discontinuity in the down payment ratio at 90 m^2 was further stressed in two new policies, "*9.27 Housing Finance Policy*" issued in September 2007 and "*New National Article Ten*" issued in April 2010 (Ministry of Finance, PRC, 2008; State Council, PRC, 2010).

[2] There are other studies in China employing RD designs to explore the effects of other preferential housing policies. For instance, Chen et al. (2019) implemented an RD design to evaluate Jinan City's "acquiring a *Hukou* by purchasing houses" policy and estimated the market value of urban *Hukou*.

[3] Painter et al. (2021) also found a significantly positive effect of housing wealth on consumption for urban households from 2002 to 2009, using household fixed-effects models. Our RD findings offer new evidence that complements their findings.

et al., 2023; Waxman et al., 2020). This is somewhat surprising, given the stylized fact that developing countries, including China, rank among the top ten in homeownership rates and price-to-income ratios globally;[4] in these countries, the high price-to-income ratios impose heavy financial burdens on low- and middle-income homebuyers upon home acquisition. Furthermore, unlike in many developed countries where financial assets constitute a larger share of household total wealth, housing wealth accounts for over 60 % of household total wealth in China, making fluctuations in housing wealth highly influential on household economic behaviors. As such, China provides an ideal setting to examine the direction and magnitude of housing-wealth effects on consumption, offering valuable insights into how housing-market policies may influence the real economy and homeowners' welfare in the developing world (Attanasio and Weber, 1994; Carroll et al., 2011; Cloyne et al., 2019).

The remainder of this paper is organized as follows. The next section reviews the relevant literature. Section 3 develops an analytical framework underlying our empirical analysis. Section 4 introduces our data. Sections 5 and 6 present and discuss our findings. The final section concludes and points out several directions for future research.

2. Relevant studies

Numerous studies have examined the relationship between housing wealth and consumption, most revealing a strong positive relationship. For instance, Case et al. (2005) furnished evidence from 14 developed countries, demonstrating sizable effects of housing wealth on consumption. Bostic et al. (2009) summarized the findings of nine studies on the marginal propensity to consume induced by increases in housing wealth, underscoring the relatively larger effects of housing wealth compared to financial wealth.[5]

While the examination of the housing wealth–household consumption relationship lies at the heart of the housing-wealth effect literature, identifying the *causal* relationship between the two variables proves challenging, primarily due to the issue of unobserved confounding (Aladangady, 2017). Common factors such as productivity and income growth may simultaneously influence housing prices and household consumption, as evidenced by the findings from the British Family Expenditure Survey (Attanasio and Weber, 1994; Attanasio et al., 2009). Campbell and Cocco (2007) found that expected changes in housing prices could affect the consumption behavior of both homeowners and renters, suggesting that housing prices are closely related to (unobserved) financial-market conditions. Households' self-selection into different locations and housing sizes could also generate a spurious relationship between housing wealth and household consumption (Li et al., 2020; Muellbauer, 2008). Ruling out the influence of these confounding factors is thus crucial for identifying the causal effects of housing wealth. This paper exploits the *unexpected* growth in housing wealth fueled by China's preferential housing policies as an exogenous shock to facilitate identification.

The literature also suggests three primary channels through which housing wealth may impact household consumption. The first entails a pure (expected) wealth effect: households increase their consumption as their housing wealth rises because they expect their future wealth to increase (Atalay and Edwards, 2022; Choi and Zhu, 2022; Munnell and Soto, 2008). The second channel involves a collateral effect: the increased housing wealth allows credit-constrained homeowners to access more (low-cost) credit (Aladangady, 2017; Defusco, 2018). The third channel concerns savings motives: rising housing values reduce the need for savings and thus increase consumption (Chamon and Prasad, 2010; Choi et al., 2017; Painter et al., 2021; Wei and Zhang, 2011). However, despite a rich literature quantifying the magnitude of the housing-wealth effect, few have attempted to disentangle these mechanisms more systematically. This study aims to elucidate these channels and provide a deeper understanding of the inner workings of the housing wealth-consumption nexus.

3. Conceptual framework and estimation strategy

To guide our empirical analysis below, this section first develops a simple model to illustrate how China's preferential housing policies may influence housing prices and household consumption among homeowners; it then develops a sharp-RD framework that underlies our empirical analysis.

3.1. Conceptual framework

A simple model helps illustrate how preferential housing policies that reduce the minimum down payment ratio and deed tax for housing units below 90 m^2 can influence housing prices and, subsequently, household consumption through households' *perceived*

[4] Nine developing countries rank among the top ten countries or regions worldwide with the highest property price-to-income ratios in 2024. These countries (with their respective property price-to-income ratios in parenthesis) include Sri Lanka (36), China (29.6), Lebanon (27.4), Philippines (27), Thailand (26.5), Vietnam (23.7), Iran (22.4), Argentina (21.1) amd Nigeria (21.1). Regarding homeownership, China ranks 10th in the world in terms of its homeownership rate. Data source of the global price-to-income ratio: https://www.numbeo.com/quality-of-life/rankings_by_country.jsp?title=2024&displayColumn=5 (accessed: April 6, 2025)

[5] It is worth noting that not all empirical studies found a positive housing-wealth effect on household consumption (Buiter, 2008; Phang, 2004; Waxman et al., 2020). For households planning to live in a dwelling for a long time, the positive effect of higher current and permanent wealth as an asset may be offset by the negative effect of increased living costs in the future (Flavin and Nakagawa, 2008; Sinai and Souleles, 2005). This argument aligns with the framework based on the permanent income hypothesis (Campbell and Cocco, 2007; Friedman, 1957; Hall, 1978). In that case, the direction in which housing wealth growth will affect consumption is unclear. Furthermore, it may be difficult for homeowners to realize the benefits brought by rising housing prices due to the unavailability of realized capital gains (Muellbauer, 2008).

housing wealth.

A. Housing Market with Down Payment and Deed Tax. Consider a housing market for units with floor areas around 90 m^2. Let P denote the housing price per unit, and h be the housing size (h is fixed at around 90 m^2). A representative household purchasing one unit is subject to a deed tax τ.[6] The total cost of a one-time purchase of this unit is thus $(1+\tau)Ph$.The buyer must also make a minimum down payment at ratio $\theta \in (0,1)$. As such, the upfront cost is $\theta(1+\tau)Ph$, with the remaining $(1-\theta)(1+\tau)Ph$ borrowed from a bank at interest rate r.

Let a denote the household's available liquid assets. Assume that households are heterogeneous in liquidity assets, the cumulative distribution function of which is represented by $F(a)$. A household can afford the upfront cost if $a \geq \theta(1+\tau)Ph$. Hence, the market demand for a size-h unit, $D(P)$, is:

$$D(P,\theta,\tau) = 1 - F(\theta(1+\tau)Ph). \tag{1}$$

It can be easily derived that:

$$\frac{\partial D}{\partial P} < 0,\ \frac{\partial D}{\partial \theta} < 0,\ \frac{\partial D}{\partial \tau} < 0. \tag{2}$$

The latter two imply that lowering either the down payment ratio θ or the deed tax τ increases the number of potential buyers that can afford a size-h unit by relaxing the liquidity constraint.

Let $S(P)$ denote the housing supply function, with $S'(P) > 0$. The market-clearing condition for an equilibrium housing price $P^*(\theta,\tau)$ satisfies:

$$D(P^*(\theta,\tau),\theta,\tau) = S(P^*(\theta,\tau)) \tag{3}$$

A simple comparative statics analysis unveils the impact of preferential housing policies on the equilibrium house price, as summarized in the following Lemma:

Lemma 1. *Reducing the down payment ratio θ or the deed tax τ will lead to a higher equilibrium housing price P^*.*

Proof. Applying the implicit function theorem to the market-clearing condition (3) yields:

$$\frac{\partial P^*}{\partial \theta} = \frac{\partial D/\partial \theta}{\partial S/\partial P - \partial D/\partial P} < 0,\ \frac{\partial P^*}{\partial \tau} = \frac{\partial D/\partial \theta}{\partial S/\partial P - \partial D/\partial P} < 0. \tag{4}$$

In words, the equilibrium housing price P^* increases as θ or τ decreases.

B. Two-Period Consumption Problem. We now investigate how a policy-induced increase in housing prices affects current consumption (c_1) for households that had already purchased their housing with size h before housing policy changes.

Without loss of generality, assume that a representative household lives for two periods, "current" ($t=1$) and "future" ($t=2$), and allocates its consumption across the two periods.[7] Let c_1 and c_2 denote consumption in periods 1 and 2, respectively. The household maximizes its utility:

$$\max_{\{c_1,c_2\}} U = u(c_1) + \delta v(c_2),\ \delta \in (0,1), \tag{5}$$

where the sub-utility functions $u(\cdot)$ and $v(\cdot)$ are concave, satisfying $u'(\cdot) > 0$, $u''(\cdot) < 0$, $v'(\cdot) > 0$, and $v''(\cdot) < 0$. The optimization is subject to the following intertemporal budget constraint:

$$c_1 + \frac{c_2}{1+r} \leq y_1 + \frac{y_2}{1+r} + \frac{P(\theta,\tau)h}{1+r}, \tag{6}$$

where y_1 and y_2 are (labor) incomes received in periods 1 and 2, respectively. The long-run (lifetime) housing wealth will be affected by the increase in equilibrium housing price $P(\theta,\tau)$ induced by housing policy changes. The homeowner smooths its consumption between periods 1 and 2 by reallocating the total exogenous income and the future housing wealth between the two periods. To maximize the total lifetime utility (5), the budget constraint will be binding in equilibrium.

Substituting out $c_2 = (1+r)y_1 + y_2 + P(\theta,\tau)h - (1+r)c_1$, we can derive the utility-maximization condition:

$$u'(c_1) = \delta v'[(1+r)y_1 + y_2 + P(\theta,\tau)h - (1+r)c_1] \tag{7}$$

The following Proposition summarizes the impact of housing policy changes on the current consumption of a representative homeowner owning a size-h housing unit.

[6] Although nine types of taxes are currently involved in real estate transactions in China, buyers are only responsible for paying the deed tax. Therefore, we simplify the transaction tax in the model by considering only the deed tax τ.

[7] Here, we assume that the mortgage loan was fully repaid before the preferential housing policy was implemented. Including the mortgage in our intertemporal budget constraint does not alter our main results.

Proposition 1. *When the preferential housing policy reduces the down payment ratio θ and the deed tax τ for a housing unit below size h, a representative homeowner will increase its current consumption c_1, that is,* $\frac{dc_1}{d\theta} < 0$, $\frac{dc_1}{d\tau} < 0$.

Proof. Applying the implicit function theorem yields:

$$\frac{dc_1}{d\theta} = \frac{\delta v'' \cdot P'(\theta,\tau)h}{u''(c_1) + \delta(1+r)v''} < 0, \quad \frac{dc_1}{d\tau} = \frac{\delta v'' \cdot P'(\theta,\tau)h}{u''(c_1) + \delta(1+r)v''} < 0. \tag{8}$$

In words, an increase in housing wealth resulting from the housing policy changes raises current consumption among homeowners with housing size *h*. Intuitively, from the intertemporal budget constraint (6), an increase in lifetime housing wealth, $P(\theta,\tau)h$, due to decreases in the down payment ratio θ and the deed tax τ, expands the lifetime budget, allowing lifetime consumption to increase. But since the period-specific sub-utility functions $u(\cdot)$ and $v(\cdot)$ are both increasing functions of period-specific sub-utility, the utility-maximization condition, Eq. (7), suggests that only an increase (rather than a decrease) in c_1 can balance the two sides of the equation to accommodate an increase in $P(\theta,\tau)h$. And since the changes in θ, τ, and $P(\theta,\tau)$, do not work through the interest rate *r*, no substitution effects are triggered. The model can be easily extended to incorporate households' savings motive as a working channel of the housing-wealth effect (Appendix 1).

3.2. Sharp-RD design

The *unexpected* changes in China's housing policies from 2006 to 2010 created a discontinuity in the down payment ratio and property deeds tax for purchased housing units with different sizes around the policy cutoff at 90 m^2. As illustrated in the conceptual model (part A) above, the reduced financial burden due to lowered property deeds tax and down payment ratios are expected to trigger a surge in housing demand for units under or equal to 90 m^2, resulting in faster housing price growth for such units (Li et al., 2020, 2023).[8] This motivates a sharp-RD design around the 90-m^2 cutoff to evaluate the effect of this policy change.

In our setting, a household *i*'s treatment status T_i, is defined based on its housing size h_i, the treatment assignment variable, in relation to the 90-m^2 cutoff:

$$T_i = \begin{cases} 1, h_i \le 90 \\ 0, h_i > 90 \end{cases} \tag{9}$$

As noted above, households that purchased units smaller than or equal to 90 m^2 before 2006 comprise the treatment group; those with units over 90 m^2 are the control group.

Under the assumption that all relevant factors except the treatment (T_i) vary smoothly at the policy threshold, the effect of policy-induced housing-wealth growth on a given outcome of interest (at the cutoff) can be captured by the following estimator:

$$\widehat{\delta} = \lim_{h\uparrow 90} \mathrm{E}(Y_i|h_i = 90) - \lim_{h\downarrow 90} \mathrm{E}(Y_i|h_i = 90), \tag{10}$$

where the outcome variable Y_i denotes consumption expenditure or the growth rate of housing wealth; $\lim_{h\uparrow 90} \mathrm{E}(Y_i|h_i = 90)$ is the left-hand limit as the assignment variable h_i approaches the 90-m^2 cutoff from below; $\lim_{h\downarrow 90} \mathrm{E}(Y_i|h_i = 90)$ is the right-hand limit as h_i approaches the cutoff from above. The difference between the two limits, $\widehat{\delta}$, provides a sharp-RD estimator of the effect of the preferential housing policies on *Y* (at the cutoff).[9]

The estimator $\widehat{\delta}$ defined in Eq. (10) can be implemented either parametrically or non-parametrically. The nonparametric approach uses local polynomial regressions to estimate the left- and right-hand limits of the outcome *Y* at the cutoff based on kernel weights for the chosen optimal bandwidth (Hahn et al., 2001):

[8] The average housing value for *just-ineligible* households with floor areas of 91-100 m^2 was 539,250 Chinese yuan (81,458 US dollars) over the sample period (2010-2018). A 2% deed tax cut would lead to a decrease in total housing costs of 10,785 yuan (1,629 US dollars). A 10% reduction in the down payment ratio will further reduce the upfront costs by 52,847 yuan (7,983 US dollars), based on the adjusted deed tax rate. As such, these preferential housing policies directly lower the financial burden by 63,632 yuan (9,612 US dollars) for *just-ineligible* households—equivalent to about 1.34 times the average household income (47,495 yuan or 7,174 US dollars) of these households, suggesting a potentially large influence these policies can have on Chinese households. A caveat is, however, that we cannot isolate the individual effects of reduced down payment ratio and deed tax because our data only begins at 2010. We thank an anonymous reviewer for pointing out this limitation.

[9] One might suggest directly estimating the effect of housing wealth on household consumption using the instrumental variable (IV) approach, i.e., regressing household consumption on housing wealth using the policy treatment (T_i) as an IV for the latter while controlling for a flexible function of housing size on either side of the cutoff. However, housing size itself, even if flexibly controlled for, may affect household consumption through channels other than housing wealth—for instance, lower-income households often choose smaller units, thus violating the exclusion restriction. Therefore, we separately estimate the effects of preferential housing policies on housing prices and household consumption using a sharp-RD design, and then compute the marginal propensity to consume out of housing wealth (MPCH) based on these two estimates in Section 5.

$$\min_{\alpha,\delta,\gamma,\eta} \sum_{i=1}^{n} K\left(\frac{h_i - 90}{b}\right)[Y_i - \alpha - \delta T_i - \gamma(h_i - 90) - \eta T_i(h_i - 90)]^2, \quad (11)$$

where b is the bandwidth and $K(\cdot)$ is a triangular kernel function. We calculate the optimal bandwidth b^* using the method proposed by Calonico et al. (2020).[10] Once b^* is determined, $\widehat{\delta}$ is estimated using the n observations around the 90-m^2 cutoff within that optimal bandwidth; α, γ, and η are regression coefficients to be estimated.

One can also implement $\widehat{\delta}$ as a parametric estimator. Our primary specification uses a flexible function of the centralized assignment variable, $\widetilde{h_i} = h_i - 90$, on both sides of the cutoff:

$$Y_i = \alpha + \delta \cdot T_i + \gamma \cdot f(\widetilde{h_i}) + \varepsilon_i, \quad (12)$$

where $f(\widetilde{h_i})$ is a polynomial function of $\widetilde{h_i}$, involving the linear and quadratic terms of $\widetilde{h_i}$ and their interactions with the treatment dummy T_i. The optimal bandwidths derived from the approach devised by Calonico et al. (2020) are used as the analytical bandwidth to mitigate bias from using many observations far from the cutoff (Lee and Lemieux, 2010). Conditional on $f(\widetilde{h_i})$ being flexible, ε_i is an independently and identically distributed (i.i.d.) error term. In the parametric model (12), the effect of preferential housing policies is captured by the coefficient of T_i, δ.

3.3. Implementation

In the analysis reported below, we estimated δ nonparametrically using "residualized" outcomes. With a valid RD design, controlling for baseline covariates can improve efficiency while maintaining the consistency of the estimator (Lee and Lemieux, 2010). We thus adopt the two-step residual method in estimation, which also addresses the issue of selecting the optimal bandwidth with the presence of covariates. Specifically, we first "residualized" the outcome variable Y by subtracting the fitted values obtained from a regression that included survey-year, purchase-year, and county fixed effects, a dummy variable for multiples of 10 m^2, and the interaction terms between a set of covariates and the treatment dummy from its observed values.[11] The covariates used include personal characteristics of the oldest household member and the attributes of the housing units introduced in Section 3.2 (Table 1). We then performed RD analyses based on the residuals from the first step.[12]

The polynomial orders were selected based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC); those with minimum AIC and BIC values are usually preferred (Lee and Lemieux, 2010). The AIC and BIC values against the corresponding polynomial orders of housing size (Table A1) from "pilot" parametric estimations show that both AIC and BIC are minimized with 2nd-order polynomials. Our nonparametric RD estimations thus adhere to the preferred 2nd-order polynomials.

Note finally that most sampled households reported their housing size as an integer, which could have generated rounding errors in the assignment variable and resulted in inconsistent RD estimates (Barreca et al., 2016). To address this issue, we adopted Dong's (2015) approach and performed sharp-RD estimations after reducing each reported housing size by 0.5 m^2. Moreover, to account for the possible autocorrelation of errors across waves for the same housing units, we clustered the standard errors at the housing-size level. Finally, we present the bias-corrected RD estimates as proposed by Calonico et al. (2014).

4. Data

4.1. Data source

Our main analysis draws data from the China Family Panel Studies (CFPS), a (nearly) nationally representative, biennial longitudinal survey covering 25 of 32 province-level regions in mainland China, where, as of 2010, 95 % of the Chinese population resided (Xie and Zhou, 2014). The survey, launched in 2010 by the Institute of Social Science Survey at Peking University, used a three-stage (county or equivalent, village or equivalent, and household) probability proportional sampling strategy with implicit stratification to select sample households (Xie and Lu, 2015). The baseline survey covered nearly 15,000 households, and 33,600 individuals residing in these households were interviewed. Follow-up waves were conducted in 2012, 2014, 2016, and 2018.

The CFPS collected data on individual, household, and community characteristics. The information collected includes the living conditions, housing status, household income, assets, and consumption expenditures of sampled households, as well as the demographic and socioeconomic characteristics of all household members. Particularly important for our study, the CFPS recorded rich details about the ownership, size, purchase time, and initial and current market values of sampled households' housing units. These

[10] In the analysis, the optimal bandwidths for all benchmark nonparametric estimations are chosen based on a common CER-optimal bandwidth selector. We test the sensitivity of the results using the common MSE-optimal bandwidth selector ("Mserd") and two different MSE-optimal bandwidth selectors ("Msetwo") proposed by Calonico et al. (2014) in our robustness checks below.

[11] Considering the clear pattern of "bunching" at multiples of ten in our assignment variable, we included a dummy variable indicating whether the reported housing size is a multiple of ten to account for the bunching effect.

[12] If the RD design is valid, this two-step procedure can provide a consistent estimate of the same RD parameter of interest and reduce the sample variability (Lee and Lemieux, 2010).

Table 1
Variable definitions and descriptive statistics, households with housing units purchased before 2006.

Variables	Definitions	A. Full sample			B. 85 m^2 ≤ housing size ≤ 95 m^2		
		(1) Treatment group (≤90 m^2)	(2) Control group (>90 m^2)	(3) Difference (3)=(1)-(2)	(4) Treatment group [85 m^2, 90 m^2]	(5) Control group (90 m^2, 95 m^2]	(6) Difference (6)=(4)-(5)
Outcome variables							
Household consumption expenditure	Sum of all consumption expenditure subcategories in the previous year (yuan)	44,729	56,659	-11,930***	50,853	46,772	4081
		(33,615)	(41,625)	(890.7)	(36,301)	(25,289)	(2849)
Annualized growth rate of housing price	$(\text{Current price/purchasing price})^{1/(\text{housing age})} - 1$	0.143	0.119	0.024***	0.123	0.125	-0.002
		(0.113)	(0.065)	(0.003)	(0.081)	(0.055)	(0.007)
Annualized growth rate of housing value	$(\text{Current value/purchasing value})^{1/(\text{housing age})} - 1$	0.141	0.116	0.025***	0.121	0.128	-0.007
		(0.112)	(0.065)	(0.003)	(0.079)	(0.063)	(0.007)
Key explanatory variable							
Housing size	Housing construction area (m^2)	63.38	118.6	-55.20***	88.58	93.07	-4.489***
		(16.73)	(33.85)	(0.578)	(1.775)	(1.507)	(0.144)
Channel variables							
Net household income	Sum of household wage, property, transfer, and operating income last year (yuan)	45,048	58,640	-13,592***	49,557	47,477	2080
		(50,603)	(68,895)	(1398)	(58,469)	(50,165)	(4737)
Housing mortgage amount	Sum of housing mortgage last year (yuan)	13,799	23,167	-9368***	16,616	13,942	2674
		(80,230)	(119,398)	(2320)	(78,949)	(68,823)	(6416)
Savings rates	Log (net household income/ household consumption expenditure)	0.118	0.050	0.068***	0.060	0.115	-0.055
		(0.907)	(0.991)	(0.026)	(0.947)	(0.780)	(0.086)
Predetermined variables							
Age	Age (in years) of the oldest household member	58.75	55.75	3.003***	57.01	54.53	2.483**
		(13.64)	(13.33)	(0.342)	(13.47)	(13.97)	(1.136)
Gender	=1 if the oldest household member is male, 0 otherwise	0.620	0.622	-0.002	0.637	0.570	0.067*
		(0.485)	(0.485)	(0.012)	(0.481)	(0.496)	(0.041)
Education	Years of schooling of the oldest household member	8.502	9.131	-0.629***	8.703	9.500	-0.797*
		(4.771)	(5.131)	(0.124)	(5.259)	(4.936)	(0.435)
Marital status	=1 if the oldest household member is married, 0 otherwise	0.800	0.860	-0.060***	0.871	0.812	0.059**
		(0.400)	(0.348)	(0.009)	(0.336)	(0.392)	(0.029)
Family size	Number of members in the household	3.059	3.654	-0.595***	3.406	3.326	0.081
		(1.395)	(1.543)	(0.036)	(1.467)	(1.146)	(0.118)
Welfare housing	=1 if yes, 0 otherwise	0.389	0.157	0.233***	0.211	0.210	0.002
		(0.488)	(0.364)	(0.011)	(0.409)	(0.408)	(0.035)
Housing cost	Housing value when the house was purchased (10,000 yuan)	5.629	11.80	-6.172***	8.796	11.04	-2.242***
		(7.353)	(11.81)	(0.228)	(9.098)	(7.631)	(0.758)
Housing age	Years since the house was purchased (year)	18.07	15.74	2.333***	17.40	12.84	4.555***
		(8.683)	(8.066)	(0.208)	(8.311)	(5.572)	(0.649)

Notes: The treatment group represents households with housing units below or equal to 90 m^2, and the control group denotes households with housing units over 90 m^2. Household consumption expenditure is calculated as the sum of all consumption expenditure subcategories, each of which is winsorized at the 98th percentile. Standard deviations (columns 1, 2, 4, and 5) and standard errors (columns 3 and 6) are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Data source: CFPS 2010–2018 waves.

variables greatly facilitate our analysis of the impact of rising housing wealth on household consumption and likely working channels.

One important limitation of the CFPS data is its lack of information for checking the balancedness of predetermined variables before 2006 in RD analysis, as the earliest wave of CFPS was conducted in 2010. As a remedy, we resort to data from the Urban Household Survey (UHS), a large, annual longitudinal dataset that tracks the socio-demographic characteristics, housing, income, and consumption information of urban households in China.[13] Four UHS waves (2002–2005) were used to test whether the socioeconomic characteristics of the "treatment" (policy-affected) and "control" households were comparable before 2006.

4.2. Sample

Several restrictions were applied to form a suitable analytic sample. First, since the preferential housing policies under discussion apply only to China's urban housing market, we confine our analysis to urban Chinese households. Second, we excluded households that purchased units in and after 2006 to circumvent potential household manipulation of housing size. Issued in 2006, *National Article Six* introduced housing policies in favor of first-time purchases of smaller housing units. Since this policy was widely considered "*unexpected*," it would be difficult for households to precisely target units just below or equal to the 90-m^2 cutoff before the policy's issuance (Li et al., 2020; 2023). After 2006, however, it became possible for households to deliberately purchase units slightly below or equal to 90 m^2, thereby enjoying both a decent housing size and faster housing-wealth growth rates endowed by the policy. As such, households with post-2006 home purchases might be subject to possible housing-size manipulation and were thus excluded. After further excluding households with missing or outlier values for housing size, purchase housing price, current housing price, and housing age at the survey year, the final sample consists of 7655 household-level observations from five CFPS waves. In the analysis, we pool sampled households from all five waves and control for survey-year fixed effects in the models.

4.3. Variables

Table 1 presents descriptive statistics for the variables used in the analysis for the full sample (panel A) and subsamples falling within $\pm$ 5-m^2 intervals around the 90-m^2 cutoff (panel B). The analysis incorporates four sets of variables. The primary outcome variables include household consumption expenditure and the annualized growth rates of housing prices and housing values (*perceived* housing wealth). Specifically, the CFPS data includes self-reported housing prices and housing values from both the year of purchase and the survey year, allowing us to compute the average annual growth rates of housing prices and housing values.[14] In our context, housing values reflect homeowners' *perceived* housing wealth: they feel richer or better endowed as residential house prices appreciate, even if they do not resell or downsize their units. The key explanatory variable is a household's treatment status T_i, defined in (9) based on its housing size measured by the construction area of the unit. To facilitate explorations of the channels driving potential housing-wealth effects, variables such as household net income, housing mortgage amount, and the savings rate are used in channel analysis. Finally, predetermined covariates, including personal characteristics of the oldest household member (such as age, gender, educational attainment, and marital status),[15] family size, whether the housing unit was part of a welfare housing program, the housing cost in the home-purchase year, and the age of the housing unit in the survey year, are used in continuity tests.

4.4. Descriptive patterns

According to (9), households with housing units below or equal to 90 m^2 comprise the treatment (policy-affected) group, and those with units exceeding 90 m^2 comprise the control group. Examining the full sample, panel A of Table 1 suggests that, on average, the treatment group enjoyed higher annualized growth rates of housing prices and housing values than the control group. Somewhat counterintuitively, the treatment group spent significantly less on household consumption than the control group. However, when focusing on households with units within the 90 $\pm$ 5 m^2 interval (the "discontinuity" sample), different patterns emerged (panel B). The average household consumption expenditure of the treatment group (50,853 yuan, approximately 7682 US Dollars) exceeded that of the control group (46,772 yuan, approximately 7065 US Dollars),[16] although the differences in the annualized growth rates of housing prices and housing values are not statistically significant.

The changes in observed patterns when moving from the full sample to the "discontinuity" sample suggest the potential influence of confounding factors. In fact, many household characteristics differ significantly between the treatment and control groups in the full sample (panel A). The differences are much less pronounced in the "discontinuity" sample (panel B), although some differences remain

[13] The UHS contains repeated cross sections, but it randomly retains about one-third of the households from the previous sample. Many studies have utilized this dataset. For example, Painter et al. (2021) used the 2002-2009 waves to explore housing-wealth effects on consumption and the precautionary-saving motives. Chamon and Prasad (2010) analyzed the 1995-2005 waves to investigate the U-shaped pattern of saving rates over the life cycle and its underlying causes.

[14] We follow Li et al. (2021) to calculate the annual average growth rate (g) of housing price: $g = (\mathit{Current\ Price}/\mathit{Purchase\ Price})^{(1/t)} - 1$, where t represents the time interval between the survey year and the home-purchase year. The average annual growth rate of housing value is similarly computed.

[15] Since our analysis is performed at the household level, we include characteristics of the oldest members in the analysis.

[16] One US dollar≈6.62 Chinese yuan in the last year of our study period (2018). Available at: https://data.worldbank.org/indicator/PA.NUS.FCRF?locations=CN).

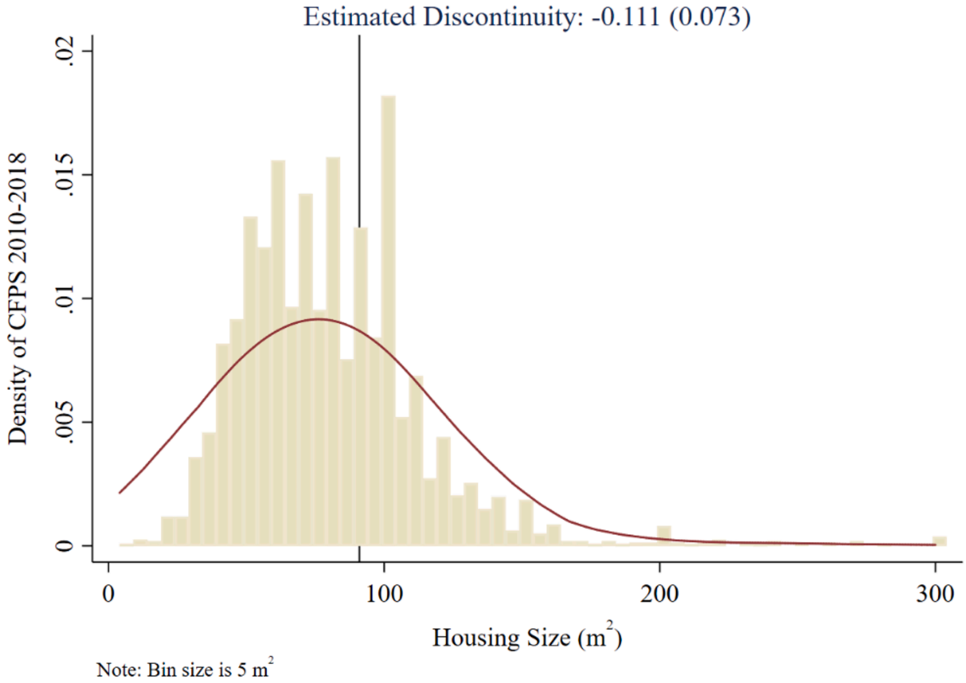


Fig. 1. Distribution of housing size
Notes: Sample = urban households with housing units purchased before 2006. Bin size = 5 m^2. Red line: the kernel density distribution (kernel = Epanechnikov). Vertical line: the cutoff point of the assignment variable (90 m^2).
Data source: CFPS 2010–2018 waves.

statistically significant. Thus, an estimation method that can properly control for potential confounding factors is needed to identify the effect of preferential housing policies and the resulting increases in housing wealth. The sharp-RD design developed in Section 3.2 serves this purpose.

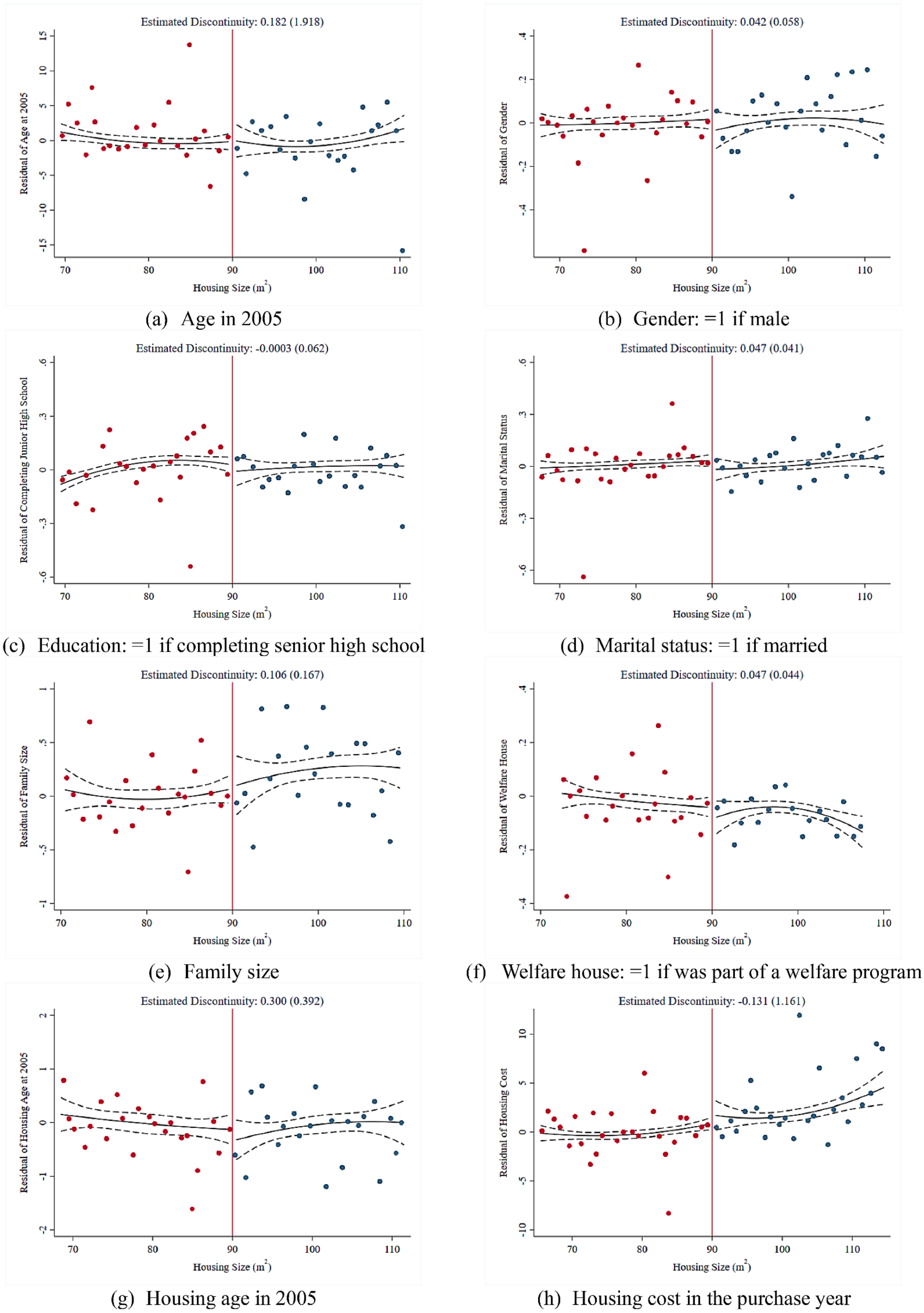
5. Results

5.1. Validity of the RD design

Before reporting the main findings of this study, it is helpful to assess the validity of our RD design, which relies on two fundamental identifying assumptions (Lee and Lemieux, 2010). The first requires that the assignment variable (housing size) not be precisely manipulated by sampled households. The second demands the continuity of households' predetermined variables at the cutoff. Additionally, our identification strategy faces potential challenges from sample-selection issues—the preferential housing policies may have induced home-moving behavior. This section performs three tests to rule out potential threats.

A. Precise manipulation of housing size. To check if the assignment variable (housing size) is subject to household manipulation, we test the continuity of its density at the 90-m^2 cutoff. Fig. 1 plots the results of this test. Reassuringly, no discernible clustering in the density of the housing-size distribution is revealed on either side of the cutoff, which is confirmed by the result of a McCrary (2008) density test (*p-value* = 0.125). Further considering the longitudinal nature of our data, which may have "smoothed out" part of the clustering at the cutoff across different periods, Fig. A1 presents the density of the housing-size distribution and McCrary test results separately for each survey wave. Again, no density peaks or significant discontinuities were detected at the cutoff, further supporting the condition of "no precise manipulation of the assignment variable."

B. Continuity in predetermined characteristics. Another test examines whether factors relevant to household consumption are continuous at the cutoff. One limitation of the CFPS is that it did not begin until 2010; we are thus unable to test the continuity of relevant household characteristics before policy enactment in 2006. Yet, we can still test the continuity of *time-invariant* variables recorded before 2006, as done by Li et al. (2020). Specifically, we test the continuity of characteristics of the oldest household member, including age in 2005, gender (dummy, =1 if male), educational attainment (dummy, =1 if completed senior high school), marital status (dummy, =1 if married), household size, along with housing unit characteristics (i.e., whether the unit was part of a welfare



(a) Age in 2005
(b) Gender: =1 if male
(c) Education: =1 if completing senior high school
(d) Marital status: =1 if married
(e) Family size
(f) Welfare house: =1 if was part of a welfare program
(g) Housing age in 2005
(h) Housing cost in the purchase year

Fig. 2. Tests for continuity in predetermined variables.
Notes: Sample = urban households with housing units purchased before 2006. The bandwidth is calculated using the CER-optimal bandwidth selection method; the number of bins is selected according to the ESMV method (mimicking the variance evenly-spaced method using spacing estimators). Circles: means of the respective variable for each bin after controlling for a dummy for multiples of 10 m^2, survey-year, purchase-year (except for housing age at 2005), and county fixed effects. Solid lines: fitted values from local linear regressions with optimal bandwidths; dashed lines represent 95 % confidence intervals. Vertical line: the cutoff of the assignment variable (90 m^2). Data source: CFPS 2010–2018 waves.

housing program, housing cost in the home-purchase year, and house age in 2005) at the cutoff. Reassuringly, none of these variables jumps at the cutoff (Fig. 2, panels a-h), further strengthening the validity of our RD design.[17]

Another way to test whether the socioeconomic characteristics of the treated and control households are balanced *ex ante* at the cutoff is to resort to other datasets that contain household information prior to 2006. We leverage four waves (2002–2005) of the Urban Household Survey conducted before 2006 to perform additional tests. Eight predetermined variables available in the UHS data are examined: the household head's age in years, gender (dummy, =1 if male), educational attainment (dummy, =1 if completed senior high school), ethnicity (dummy, =1 if Han), marital status (dummy, =1 if married), family size, whether the household had other housing units, and its savings rate. The results again revealed no notable discontinuities at the cutoff (Fig. A2, panels a-h).

C. Households' moving behavior. Although we have limited the analytic sample to households that purchased housing units before 2006, the data came from surveys conducted after 2006 (2010–2018), which raises a concern about self-selection issues: the preferential policies under discussion may have created differential incentives for (unrecorded) home-moving on the two sides of the cutoff between sampled households' home-purchase year and the survey date. If the policies induced some households to move in or out of their units around the 90-m^2 cutoff after 2006, those just below and above 90 m^2 may no longer be comparable.

Two questions asked in the CFPS help address this concern: "When did you move into your current dwelling?" (only asked in CFPS-2010), and "Is your family currently living in the same dwelling as the one in the previous survey?" (asked in CFPS-2014 through CFPS-2018). We used the answers to these questions to test the discontinuity in households' home-moving behavior. Again, no notable jumps in household moving occur at the cutoff (Fig. 3), which greatly alleviates concerns about sample-selection issues.

5.2. *Main findings: housing-wealth effects on household consumption*

Turning to the main findings of this paper, we first report the impacts of the preferential housing policies (2006–2010) on the growth rates of housing prices and housing values between the two sides of the policy cutoff at 90 m^2. We then estimate the impact of these policies on household consumption. Similar jumps in both outcome variables at the cutoff will provide corroborative evidence of the impact of housing wealth on household consumption.

A. Effects on housing prices and housing values. Fig. 4, panel a, depicts the relationship between housing size and the annualized growth rate of housing prices, showing a clear jump in the latter at the 90-m^2 cutoff. Table 2, columns 1–2, quantifies this jump: housing prices for households with units just under or equal to 90 m^2 increased by 1.8–2.0 % faster annually than for households with units just above 90 m^2. This estimate is quantitatively comparable to that of Li et al. (2020), who estimated a 1.3 % difference in the annual growth rate of housing prices at the same cutoff. Echoing the policy's effect on housing prices, Fig. 4, panel b, and Table 2, columns 3–4, reveal significant effects on the annualized growth rate of housing wealth: the average housing wealth of *just-affected* households is 1.6–2.0 % higher than that of those *just-eligible*.[18] Using the average housing value for the *just-eligible* households with floor areas of 85–90 m^2, 532,002 yuan, as a benchmark, the estimated policy impact translates into an annual increase in housing value of 8512–10,640 yuan (approximately 1286–1607 US dollars in 2018). This increase in housing value is substantial, amounting to nearly 17.9–22.4 % of the household net income for *just-ineligible* households with floor areas between 91–95 m^2.

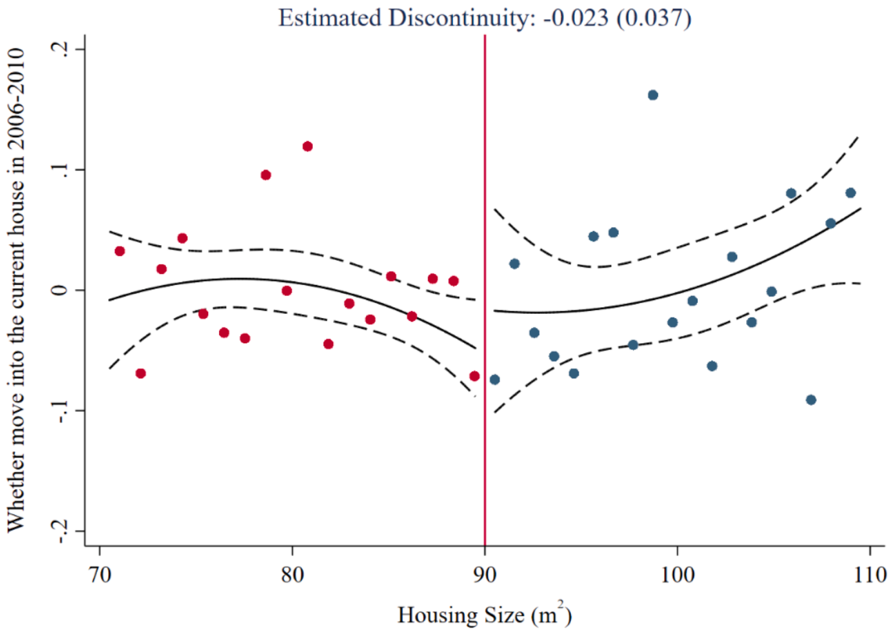
B. Effects on household consumption. Turning to this study's outcome variable of primary interest, Fig. 5 plots the relationship between housing size and household consumption expenditure. Again, regardless of the order of the polynomial functions used, a jump in household consumption expenditure at the 90-m^2 cutoff is evident: households with units just below the cutoff spent significantly more on consumption than those just above 90 m^2. Table 3, column 1, quantifies the size of this jump illustrated in Fig. 5(b): owing to the *unexpected* preferential housing policies, *just-affected* households spent 26.6 % more on consumption than those just unaffected. We interpret our RD estimates as capturing the overall effect of preferential housing policies on household consumption around the 90-m^2 cutoff, recognizing the potential for spillover effects on units just above 90 m^2. On the one hand, if housing units with areas just above 90 m^2 are located near those appreciating units below 90 m^2, the former may also experience price increases due to neighborhood spillovers or boosted confidence in the local housing market. Such a positive spillover could elevate household consumption among units with areas just above 90 m^2, rendering our RD estimate a lower bound. On the other hand, if marginal homebuyers substitute toward subsidized units equal to or just below 90 m^2, demand for units just above 90 m^2 may fall, producing a negative spillover that could lead our estimates to overstate the policy effect. However, our further RD analysis, which gradually excludes observations with floor areas above 90 m^2, generates larger impact estimates on the annualized growth rate of housing price, suggesting that the spillover effect is likely to be positive. [19] For comparison and smoothing purposes, we also employ a parametric approach to estimate the effects of preferential housing policies (2006–2010) on household consumption. The parametric estimates, especially the one with a 2nd-order polynomial (Appendix Table A3, column 4), are comparable to our nonparametric ones.

To gauge the magnitude of this effect, we calculated the marginal propensity to consume (MPC) associated with the estimated growth in housing wealth. Consider a representative household with a 90-m^2 unit, with an average consumption of 46,548 yuan and an average housing value of 425,898 yuan. A 26.6 % increase in household consumption resulting from the policy amounts to a rise of 12,382 yuan, while a 2 % increase in the annual growth rate of housing values translates into an extra 8518 yuan. This implies that for

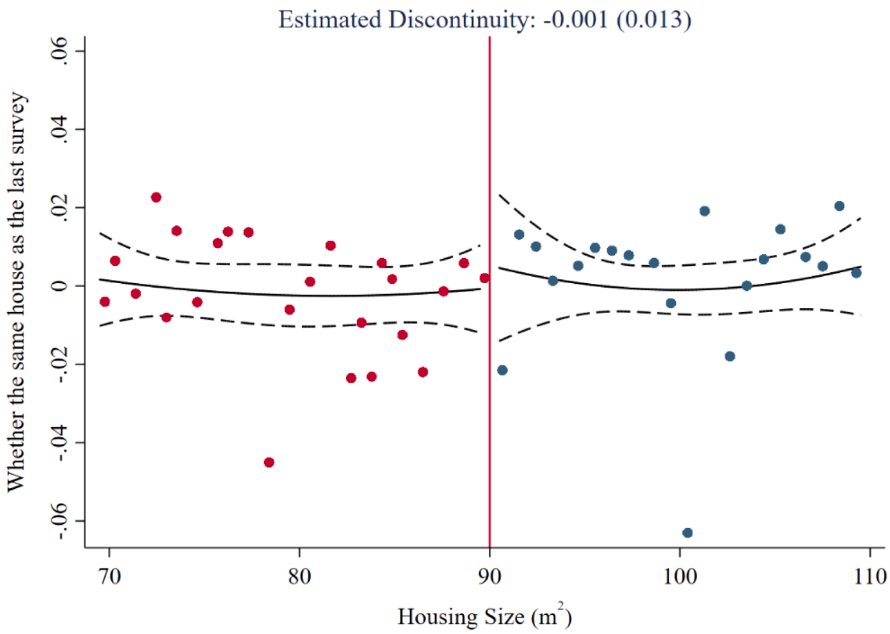
[17] Given the large number of variables examined, the jump in oldest members' education could simply be driven by random sampling errors. At the 5% level, one would expect one variable out of 20 to come out significantly even when there are no underlying discontinuities.

[18] The faster growth rate in housing value for units just below or equal to 90 m^2 results from the faster growth rate of housing price for these units. For clarity, we will refer only to housing wealth in the following discussion.

[19] We thank an anonymous reviewer for suggesting this analysis.



(a) Whether moved into the current house in 2006-2010



(b) Whether lived in the same house as in the last survey

Fig. 3. Impact on House Moving Behavior After 2010.

Notes: Sample = urban households with housing units purchased before 2006. The bandwidth is calculated using the CER-optimal bandwidth selection method, and the number of bins is selected according to the ESMV method (mimicking the variance evenly-spaced method using spacing estimators). Circles represent conditional mean values of the respective variable for each bin after controlling for survey-year (only Fig. 3b), home-purchase year, and county fixed effects, and a dummy for multiples of 10 m^2. Solid lines: fitted values from local linear regressions with optimal bandwidths; dashed lines: 95 % confidence intervals. Vertical line: the cutoff point of the assignment variable (90 m^2). Data source: CFPS 2010–2018 waves.

every one-yuan increase in housing wealth, household consumption rises by approximately 1.5 yuan (12,382/8518). As such, the MPC from housing wealth—defined as the increase in household consumption per yuan/m^2 increase in housing wealth—is roughly 0.017 (1.5 yuan/90 m^2). This estimate is slightly smaller than that of Painter et al. (2021), who found an MPC of 0.023 for urban Chinese households during the decade (2002–2009) preceding our study period based on a different dataset.

Further exploring specific consumption categories that might be affected by the policies, Table 3, columns 2–8, presents nonparametric RD estimates of the policy effects on different components of household consumption. Compared with *just-unaffected* households, those just affected spent significantly more on various consumption subcategories: 62.6 % more on clothing (column 3), 52.3 % more on daily goods (column 5), 76.1 % more on transportation and communication (column 7), and 87.7 % more on education and entertainment (column 8). In contrast, food, living,[20] and healthcare expenditures were not significantly different across the cutoff. The sharp increases in education and entertainment expenditures are consistent with the estimates of Li et al. (2023), who found that urban China's preferential housing policies (2006–2010) substantially boosted household spending on cultural, entertainment, and leisure activities among families with children (up to age 18 in 2006).[21] Furthermore, the considerable increase in transportation and communication expenditures might suggest that those *just-affected* households are incurring substantial costs related to purchasing and maintaining new vehicles. As shown in Appendix Fig. 3A, the probability of car purchases among *just-affected* households has significantly increased by 16.2 %. Importantly, these findings suggest a significant improvement in the consumption structure for homeowners with smaller units, as *just-affected* households allocated a larger share of their spending to developmental categories rather than necessities with less elastic demand, such as food.[22]

5.3. Long-term effects

In response to the rapid rise in housing prices after 2010, the Chinese government introduced several policies (e.g., those related to land supply, mortgages, and housing speculation) to cool down an overheated housing market. If any of these measures were tied to the 90 m^2 cutoff, they could have influenced the effectiveness of the preferential housing policies under evaluation. Upon reviewing policies related to the 90-m^2 cutoff, we identified only one additional preferential policy involving the 90 m^2 cutoff during the study period (2010–2018).[23] In February 2016, the Ministry of Finance, the State Taxation Administration, and the Ministry of Housing and Urban-Rural Development of China jointly issued a document stipulating that the property deed tax rate be levied at a reduced rate of 1 % for first-time purchases of units below or equal to 90 m^2, and at a reduced rate of 1.5 % for units above 90 m^2.[24] This policy potentially diminished the benefits of purchasing smaller units and counterbalanced the stimulative effect of earlier preferential housing policies issued before 2010. Therefore, it is informative to examine the persistence of housing-wealth effects by dividing our analytical sample into a short-term subsample (including the 2010–2014 waves) and a long-term subsample (including the 2016 and 2018 waves). Consistent with our reasoning, although the estimated effect on household consumption is smaller in the long term (Table 4, column 2) than in the short term (Table 4, column 1), it remains significantly positive, suggesting that the pre-2010 preferential housing policies have cast a long-lasting impact on urban Chinese households' consumption dynamics after 2010, and that the 2016 policy indeed offset some of the housing-wealth effect of the 2006 policy.

5.4. Robustness checks

Although we have provided evidence supporting the identification assumptions underlying our RD design, there may still be threats to the validity of our findings. This subsection performs a series of additional checks.

A. The role of housing supply. The effects of the preferential housing policies (2006–2010) are likely to differ depending on housing supply conditions. *National Article Six* explicitly emphasized that for all newly approved and commenced commercial housing projects, units under or equal to 90 m^2 must constitute more than 70 % of the total construction area starting from June 1, 2006 (also known as the "90/70 policy"). This policy change implies an increased supply of units under or equal to 90 m^2, driven either by developers' adherence to the policy or their anticipation of higher demand for smaller units. As such, the observed rise in housing prices reflects an

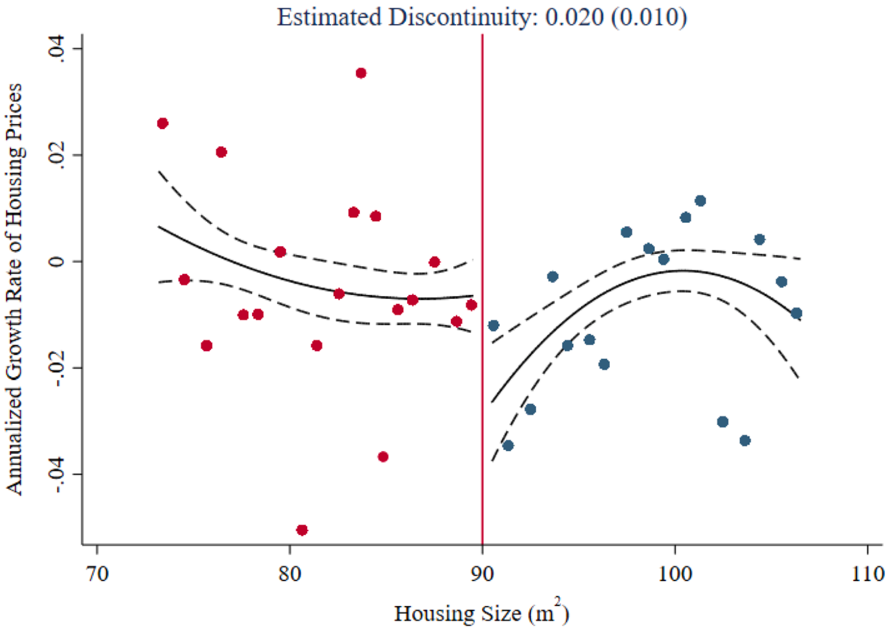
[20] Household living expenditure includes rental expenses (excluding housing mortgage) and living expenses (such as property management and heating fees). Housing mortgage and expenditures for purchasing or constructing housing units are not included in the household consumption expenditure.

[21] We thank an anonymous reviewer for pointing this out. The main sample analyzed by Li et al. (2023) was restricted to households with children up to age 18 in 2006, whereas our study did not impose this sample restriction. This difference might explain why Li et al. (2023) observed a significant increase only in expenditures on culture, entertainment, and leisure activities, while we found notable increases in other types of consumption as well. By comparison, our results provide a more comprehensive perspective on the housing-wealth effect on household consumption.

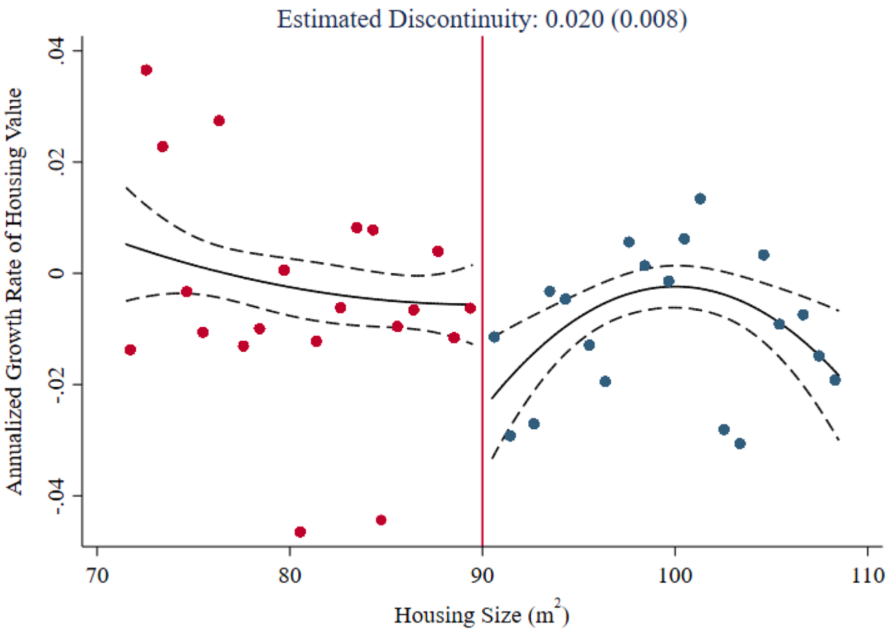
[22] Appendix Table A2 further replicates our nonparametric RD estimates of the effects of housing wealth on household consumption expenditure and its subcategories using only observations with complete consumption data. The results are consistent with those in Table 3, with the additional finding that the effect on living expenditures becomes positively significant at the 10% level.

[23] It is worth noting that before 2010, the central government issued many other housing, macroeconomic, and monetary policies. Although some focused on small and medium-sized housing units, none involved a discontinuity at the 90-m^2 cutoff. Since our RD analysis has controlled for flexible functions of housing size (as the running variable), our RD estimates should not pick up the influence of these policies.

[24] This document, entitled "*Notice on Adjusting the Preferential Policies of Deed Tax and Business Tax in Real Estate Transactions*", is still effective at the time of writing. Available at: https://www.gov.cn/xinwen/2016-02/19/content_5043891.htm?from=androidqq (accessed: May 20, 2025).



(a) Annualized growth rate of housing prices



(b) Annualized growth rate of housing values

Fig. 4. Impacts on Annualized Growth Rate of Housing Prices and Housing Values.
Notes: Sample = urban households with housing units purchased before 2006. The bandwidth is calculated using the CER-optimal bandwidth selection method, and the number of bins is selected based on the ESMV method (mimicking the variance evenly-spaced method using spacing estimators). Circles represent mean values of the annualized growth rate of housing prices (housing values) for each bin after controlling for a dummy for multiples of 10 m^2, survey-year, home-purchase year, and county fixed effects. Solid lines: fitted values from local linear regressions with optimal bandwidths; dashed lines: 95 % confidence intervals. Vertical line: the cutoff point of the assignment variable (90 m^2). Data source: CFPS 2010–2018 waves.

Table 2
Nonparametric RD estimates on annualized growth rate of housing prices and housing values.

	Annualized growth rate of housing prices		Annualized growth rate of housing values	
	(1)	(2)	(3)	(4)
$T = 1[\text{Housing size} \leq 90\ \text{m}^2]$	0.018**	0.020*	0.016***	0.020**
	(0.008)	(0.010)	(0.006)	(0.008)
Polynomial order	1	2	1	2
Optimal Bandwidth	10.17	16.84	9.83	18.71
Observations	6262	6262	6731	6731

Notes: Sample = urban households with housing units purchased before 2006. All estimations are performed by local linear regressions. Regression results are bias-corrected; kernel = triangular; bandwidth selection method = CER-optimal bandwidth selector. All regressions control for a dummy for multiples of 10 m^2, survey-year, home-purchase year, and county fixed effects. Standard errors in parentheses are clustered at the housing-size level. ***p < 0.01, **p < 0.05, *p < 0.1. Data source: CFPS 2010–2018 waves.

equilibrium between housing demand and supply for units on both sides of the 90-m^2 cutoff. This raises an important question: Are places where the demand for units of size 90 m^2 or smaller significantly exceeds their supply also experiencing more pronounced effects on household consumption?

It is natural to hypothesize that housing prices and housing values for units below or equal to 90 m^2 will increase more in areas where demand for these smaller units exceeds their supply. To test this, we compute the growth gaps in housing prices and housing values between units under or equal to 90 m^2 and those above 90 m^2 within each province, which capture, at least partly, adjustments in the supply of smaller units. We then divide our sample by the median growth gap and repeat nonparametric RD estimations separately for the low- and high-growth gap groups. The results support our hypothesis: in provinces where the preferential housing policies exerted more pronounced housing-price (Table 5, column 2) or housing-value (Table 5, column 4) effects, the effects on household consumption are indeed larger compared to provinces with relatively modest housing-price or housing-value effects.

B. Housing wealth effect or income effect? While the preferential housing policies (2006–2020) impacted household consumption in urban China, they may have induced changes in factors other than housing wealth. For instance, as found by Li et al. (2020), rising housing wealth can impact labor supply, which in turn can affect households' *current* income. To see if the observed impact on household consumption is attributable to changes in household income, we investigate whether there is a significant discontinuity in both annual household net income and household income *per capita* at the policy cutoff. As Fig. 6 shows, neither measure exhibits any discernible jump at the cutoff. Table 6 further confirms this finding, suggesting that the observed change in household consumption at the cutoff was not attributable to household income; an "*unexpected*" housing-wealth effect was a more likely cause. The absence of income responses aligns with the findings of Li et al. (2023), who found no significant effects of the same housing policies on individuals' monthly income or annual earnings.

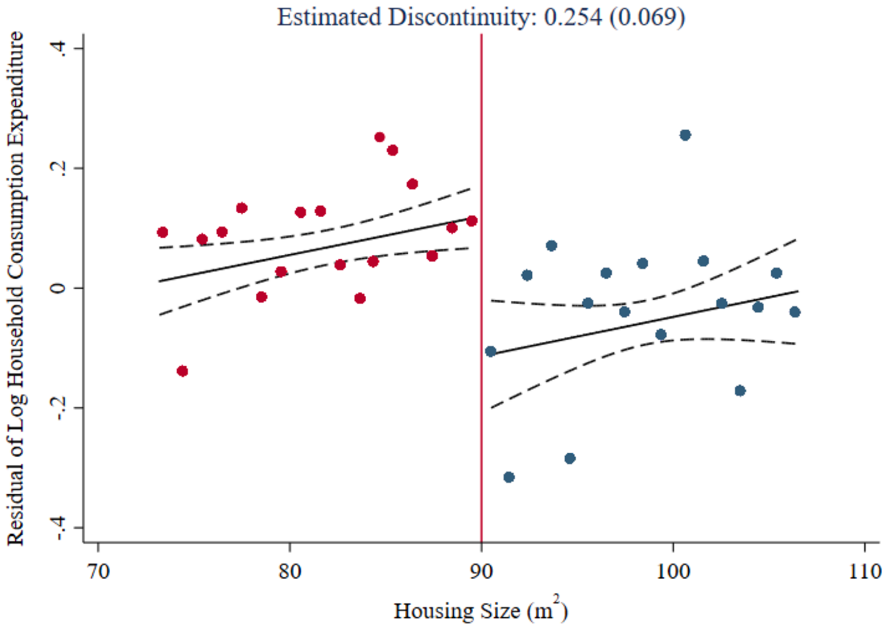
C. Alternative bandwidths and bandwidth-selection methods. Table 7, panel A, tests whether our estimated effects of the preferential housing policies on household consumption are sensitive to the choice of bandwidth. Columns 1–4 of this panel show that when the bandwidth is set at 0.5, 0.8, 1.2, and 1.5 times the optimal one (23.15, as reported in Table 3, column 1), the estimated effects of the preferential housing policies remained comparable to our original estimate in Table 3, column 1 ($\widehat{\delta} = 0.266$). Panel B, columns 5–6, shows that our estimated effect of housing policies on consumption is robust to the two additional optimal bandwidth selectors.

D. Alternative kernel and polynomial functions. Panel B, columns 7–8, checks how different kernel functions (e.g., triangular, uniform, and Epanechnikov kernels) may affect our RD estimates. The estimates remain robust to the choice of kernel functions. Recall that our baseline RD estimates were obtained based on 2$^{\text{nd}}$-order polynomial functions. Panel C, columns 9–10, checks the sensitivity of our RD estimates to different polynomial functions. The results based on 1$^{\text{st}}$-order (column 9) and 3$^{\text{rd}}$-order polynomials (column 10) are similar to our original estimate.

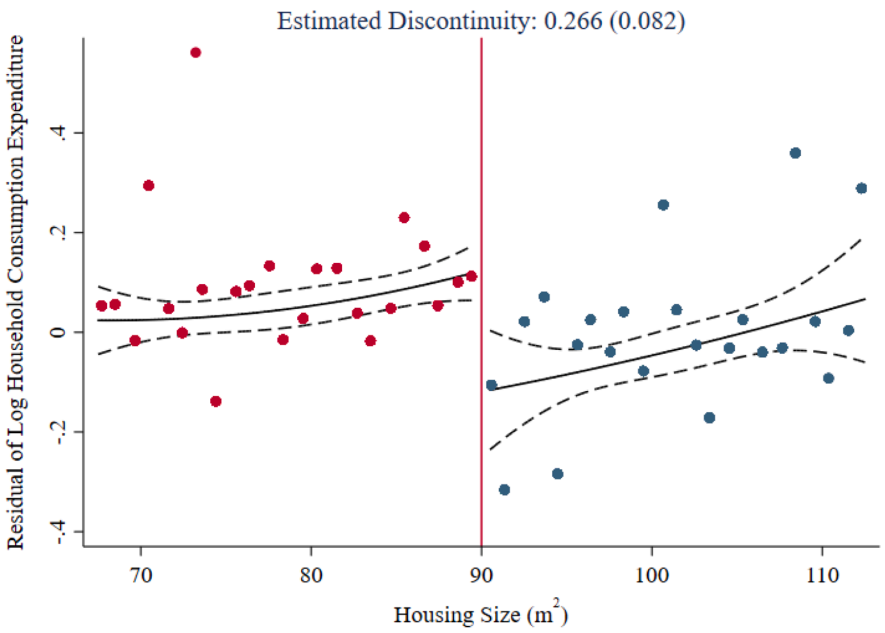
E. Placebo cutoffs. To further verify whether 90 m^2 is indeed an effective policy cutoff, we conduct a permutation test with "fake" cutoffs set at 80 m^2 and 100 m^2 and re-perform RD analyses around these cutoffs. The placebo RD estimates (Panel C, columns 11–12) are both statistically insignificant, further supporting the 90-m^2 cutoff as an effective policy cutoff.

F. Donut-hole RD estimates. During the interview, sampled households may have rounded their house size to the nearest integer. Rounding errors near the cutoff may result in misassignments of households into the treatment and control groups, leading to data-heaping bias in RD estimates (Barreca et al., 2016). To investigate this possibility, we applied a donut-hole RD design (Carneiro et al., 2015; Shigeoka, 2014), removing observations near the cutoff. Column 13 of Table 7, panel C, shows the results after removing observations with housing sizes of 90 m^2, which are nearly identical to our original RD estimate in Table 3, column 1 ($\widehat{\delta} = 0.266$). We further excluded observations with housing sizes between 89 and 91 m^2 using both triangular and uniform kernel functions.[25] The

[25] In our main RD analysis, the triangular kernel function is preferred because it assigns higher weights to observations closer to the cutoff and lower weights to those farther away from the cutoff , which is desirable given the discrete and heaping nature of our running variable (Cattaneo et al., 2020). However, there is an important trade-off with the donut-hole approach: the triangular weighting scheme will amplify the influence of more distant (and potentially noisier) observations once the more heavily weighted data points near the cutoff are removed, thus generating less stable estimates. Therefore, we employ a uniform kernel to produce more stable estimates in a donut-hole design and use a triangular kernel in the main analysis. We thank an anonymous reviewer for suggesting this discussion.



(a) First polynomial order



(b) Second polynomial order

Fig. 5. Impacts on Log (Household Consumption Expenditure).
Notes: Sample = urban households with housing units purchased before 2006. The bandwidth is calculated using the CER-optimal bandwidth selection method, and the number of bins is selected based on the ESMV method (mimicking the variance evenly-spaced method using spacing estimators). Circles represent conditional mean values of the log of household consumption expenditure for each bin after controlling for predetermined variables, a dummy for multiples of 10 m^2, survey-year, home-purchase year, and county fixed effects. Solid lines: fitted values from local linear regressions with optimal bandwidths; dashed lines: 95 % confidence intervals. Vertical line: the cutoff point of the assignment variable (90 m^2). Data source: CFPS 2010–2018 waves.

Table 3
Non-parametric RD estimates of housing-wealth effects on household consumption and subcategories.

	Log (Household consumption expenditure) (1)	Log (Food expenditure) (2)
$T = 1$[Housing size $\leq$ 90 m^2]	0.266***	0.086
	(0.082)	(0.082)
Optimal bandwidth	23.15	19.70
Observations	7478	7423
	Log (Clothing expenditure) (3)	Log (Living expenditure) (4)
$T = 1$[Housing size $\leq$ 90 m^2]	0.626**	0.361
	(0.257)	(0.244)
Optimal bandwidth	23.25	24.62
Observations	7399	7346
	Log (Daily good expenditure) (5)	Log (Healthcare expenditure) (6)
$T = 1$[Housing size $\leq$ 90 m^2]	0.523**	0.018
	(0.256)	(0.523)
Optimal bandwidth	25.07	25.31
Observations	7329	7428
	Log (Transportation & communication expenditure) (7)	Log (Education & entertainment expenditure) (8)
$T = 1$[Housing size $\leq$ 90 m^2]	0.761***	0.877***
	(0.180)	(0.204)
Optimal bandwidth	20.76	18.06
Observations	7349	7392

Notes: Sample = urban households with housing units purchased before 2006. All estimations are performed by local linear regressions. Regression results are bias-corrected; kernel = triangular; polynomial order =2; bandwidth selection method = CER-optimal bandwidth selector. Each consumption subcategory is winsorized at the 98th percentile before aggregation into total consumption. All regressions control for pre-determined variables, a dummy for multiples of 10 m^2, survey-year, home-purchase year, and county fixed effects. Standard errors in parentheses are clustered at the housing-size level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Data source: CFPS 2010–2018 waves.

Table 4
Impacts of preferential housing policies on household consumption: short term vs. long term.

Dependent variable	Log (Household consumption expenditure)	
	2010–2014 waves (1)	2016 and 2018 waves (2)
$T = 1$[Housing size $\leq$ 90 m^2]	0.304***	0.282***
	(0.093)	(0.083)
Optimal bandwidth	28.55	19.16
Observations	4800	2628

Notes: Sample = urban households with housing units purchased before 2006. All estimations are performed by local linear regressions. Regression results are bias-corrected; kernel = triangular; polynomial order =2; bandwidth selection method = CER-optimal bandwidth selector. Household consumption expenditure is calculated as the sum of all consumption expenditure subcategories, each of which is winsorized at the 98th percentile. All regressions control for pre-determined variables, a dummy for multiples of 10 m^2, survey-year, home-purchase year, and county fixed effects. Standard errors in parentheses are clustered at the housing-size level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Data source: CFPS 2010–2018 waves.

resulting donut-hole RD estimates (panel C, columns 14–15) turn out to be larger than the original estimate, suggesting that potential data heaping poses little threat to the validity of our main finding.

G. Alternative clustering methods. In our primary analysis, we cluster standard errors at the housing-size level to account for autocorrelation for the same housing units over time. However, given that housing units within the same market may exhibit intra-market correlation, we re-estimated our RD models, clustering standard errors at the county level. The results (Panel C, column 16) remain comparable under this alternative approach.

6. Mechanism analysis

The previous sections provide robust evidence that homeowners increased their consumption expenditure in response to policy-induced higher housing values in urban China. This section examines possible channels through which the identified housing-

Table 5
Differential effects on household consumption by growth gap in housing price and wealth.

Dependent variable	Log (household consumption expenditure)			
Sample	Growth gap in housing price		Growth gap in housing value	
	Low (1)	High (2)	Low (3)	High (4)
$T = 1[\text{Housing size} \leq 90\ \text{m}^2]$	0.208***	0.339***	0.178***	0.346***
	(0.071)	(0.109)	(0.067)	(0.124)
Optimal bandwidth	20.98	23.32	20.17	25.62
Observations	4004	3457	3765	3700

Notes: Sample = urban households with housing units purchased before 2006. Low (high) growth gap group in housing price refers to households in provinces where the difference in housing price growth between units under or equal to 90 m^2 and above 90 m^2 was below (above) the median growth gap. The classification of low and high growth gap groups in housing value follows the same rule as the low and high growth gaps in housing prices. All estimations are performed by local linear regressions. Regression results are bias-corrected; kernel = triangular; polynomial order =2; bandwidth selection method = CER-optimal bandwidth selector. Household consumption expenditure is calculated as the sum of all consumption expenditure subcategories, each of which is winsorized at the 98th percentile. All regressions control for predetermined variables, a dummy for multiples of 10 m^2, survey-year, home-purchase year, and county fixed effects. Standard errors in parentheses are clustered at the housing-size level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Data source: CFPS 2010–2018 waves.

wealth effects operated by exploring heterogeneity across subgroups. Specifically, we test whether rising housing values drove up household consumption through a pure-wealth effect, a collateral effect, or a reduced savings motive to understand how rising housing values may influence household consumption and what types of households are most affected.

6.1. Pure wealth effect

The life-cycle hypothesis emphasizes the age-dependent nature of household consumption patterns (Modigliani and Brumberg, 1954). To the extent that the horizon for recouping returns from rising housing wealth is shorter for older homeowners, *unexpected* wealth gains should have a more pronounced effect on older homeowners than younger ones. Thus, a stronger housing-wealth effect observed among older homeowners will provide evidence supporting a pure-wealth effect (Attanasio and Weber, 1994; Gan, 2010).

To test this hypothesis, we divide all sampled households into three age groups and explore possible between-group heterogeneity in housing-wealth effects: young households (with financial decision-makers under 45 years old), near-retirement households (with financial decision-makers between 45 and 60 years old), and retirement households (with financial decision-makers above 60).[26] The results unveil a pattern consistent with the life-cycle hypothesis (Appendix Table 8A, columns 1–3). The estimated effect for young (column 1) households is statistically insignificant, whereas those for near-retirement and retirement households (columns 2–3) are statistically significant, with the effect being largest for retirement households. This finding echoes the patterns identified by Campbell and Cocco (2007) in the U.K.

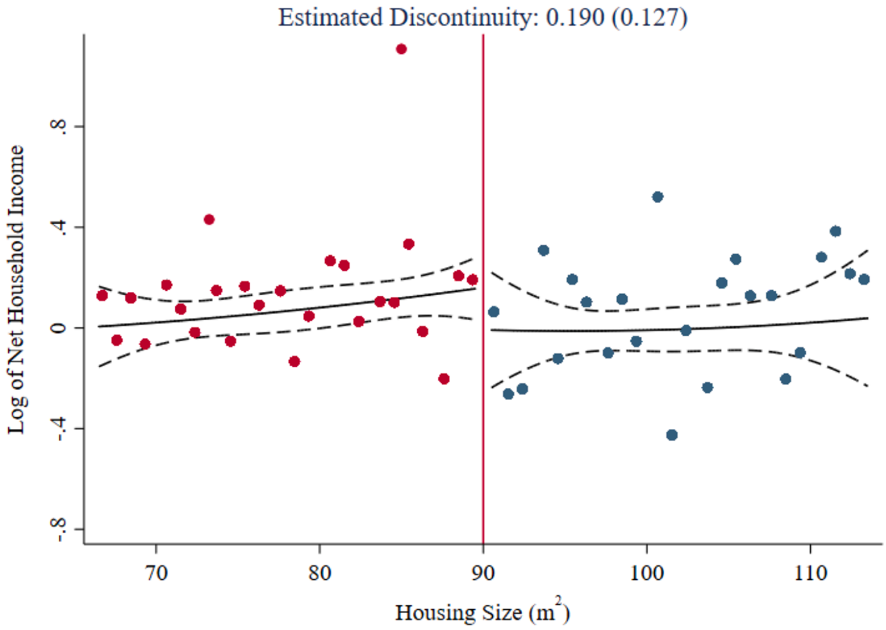
Another approach to testing the pure-wealth effect is to compare households with a single housing unit to those with multiple units. For single-unit households, the housing unit primarily serves as a durable good for self-occupancy, thereby limiting their ability to fully realize potential gains from housing asset growth. In contrast, multiple-unit households can capitalize on these gains more readily by selling or exchanging properties, even though these properties may largely represent on-paper wealth (Cloyne et al., 2019). The results, reported in columns 4–5 of Table 8A, indicate that the consumption response is both larger and more statistically significant among multi-unit households, suggesting that a pure-wealth effect is at work. Furthermore, since Fig. 3 reveals no significant house-moving behavior for homeowners after the issuance of the preferential housing policies, it appears that the wealth effect more likely operates through an *expectation* channel than through the immediate realization of wealth via property sales. The heterogeneous effect across the number of housing units is also consistent with previous findings in China. For example, Gan (2010) found that multiple-unit households have a stronger propensity to consume when housing wealth rises.

6.2. Collateral effect

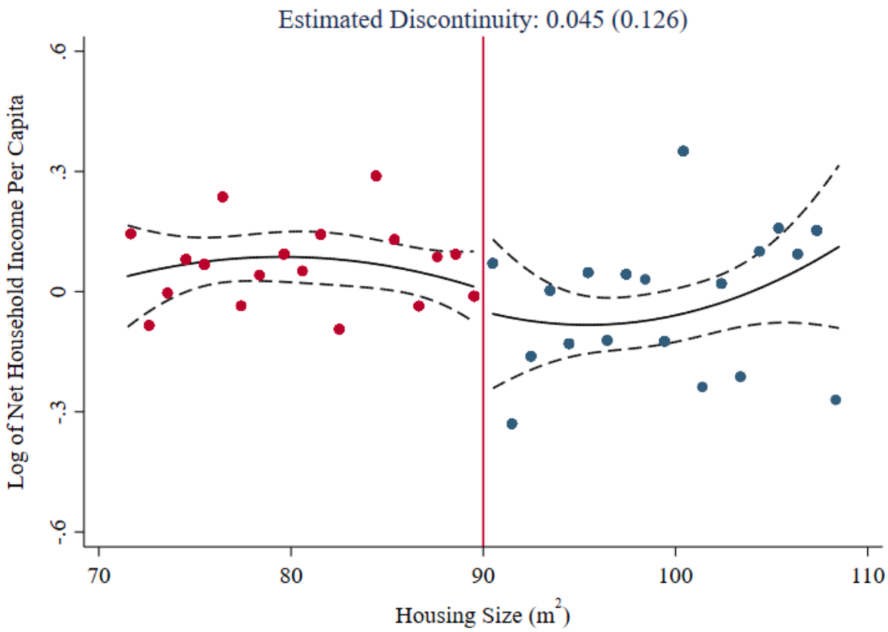
Many researchers have emphasized the collateral mechanism in explaining the effect of housing wealth on consumption (Aladangady, 2017; Cloyne et al., 2019; DeFusco, 2018). The rise in housing values is expected to amplify the market value of housing units for credit-constrained homeowners, thereby alleviating their liquidity constraints and increasing their purchasing power. To examine this mechanism, we first investigate whether the upswing of housing wealth enhanced homeowners' likelihood of securing a housing mortgage. We then compare the consumption responses between households that obtained a mortgage in the previous year and those that did not.

As shown in Table 8B, column 1, the estimated effect of the preferential housing policies on the incidence of securing a housing

[26] The mandatory retirement system in urban China sets 60 as the official retirement age for male employees and 55 or 50 for female employees during our study period (Zhang et al., 2018)



(a) Log (Household income)



(b) Log (Household income per capita)

Fig. 6. Impact on Log (Household Net Income).

Notes: Sample = urban households with housing units purchased before 2006. The bandwidth is calculated using the CER-optimal bandwidth selection method, and the number of bins is selected according to the ESMV method (mimicking the variance evenly-spaced method using spacing estimators). Circles represent mean values of the total household net income (household income *per capita*) for each bin after controlling for pre-determined variables, a dummy for multiples of 10 m^2, survey-year, home-purchase year, and county fixed effects. Solid lines: fitted values from local linear regressions with optimal bandwidths; dashed lines: 95 % confidence intervals. Vertical line: the cutoff point of the assignment variable (90 m^2). Data source: CFPS 2010–2018 waves.

Table 6
Exclusivity of income effects.

	Household net income		Household net income *per capita*	
	(1)	(2)	(3)	(4)
$T = 1[\text{Housing size} \leq 90\ \text{m}^2]$	0.169	0.190	0.063	0.045
	(0.108)	(0.127)	(0.107)	(0.127)
Polynomial order	1	2	1	2
Optimal Bandwidth	18.30	24.05	11.85	18.75
Observations	7478	7478	7257	7257

Notes: Sample = urban households with housing units purchased before 2006. All estimations are performed by local linear regressions. Regression results are bias-corrected; kernel = triangular; polynomial order =2; bandwidth selection method = CER-optimal bandwidth selector. All regressions control for predetermined variables, a dummy for multiples of 10 m^2, survey-year, home-purchase year, and county fixed effects. Standard errors in parentheses are clustered at the housing-size level. ***p < 0.01, **p < 0.05, *p < 0.1. Data source: CFPS 2010–2018 waves.

mortgage in the previous year is statistically insignificant. Moving to columns 2–3, the impact of housing wealth on consumption is also statistically insignificant for both households that obtained a new mortgage in the previous year (column 2) and those that did not (column 3). Note, however, that the point estimate of the effect is, in fact, larger in magnitude for the former, albeit less precisely estimated than our original estimate, presumably due to a smaller sample size. In any case, these findings suggest a limited role of the collateral channel in our context, which is consistent with previous studies in China. For example, Painter et al. (2021) also found limited explanatory power of the collateral channel for the observed housing-wealth effect. Note also that these findings are at odds with the collateral effect commonly found in developed countries (Aladangady, 2017; Cooper, 2013; DeFusco, 2018; Mian and Sufi, 2011). The limited role of the collateral channel found here may be due to the underdevelopment of mortgage markets in China (Painter et al., 2021).

6.3. *Reduced savings motive*

Housing wealth can also influence household consumption through changes in savings. Choi et al. (2017) noted that more than 80 % of China's high savings rate was attributed to precautionary savings. Households may *perceive* their housing wealth as a buffer against emergencies or specific significant expenses, such as large medical bills or college tuition for their children. As such, a positive housing-wealth shock may weaken households' motivation for precautionary savings and increase their consumption (Gan, 2010; Painter et al., 2021; see also Appendix 1). Moreover, the seminal work by Wei and Zhang (2011) argues that the competitive-saving motive induced by the male-biased sex ratio accounts for about half the actual increase in Chinese households' savings rate. If such a competitive-saving motive exists, we would expect more pronounced housing-wealth effects for households residing in regions with lower sex ratios.

To test whether a reduced savings motive is at play, we first examine whether rising housing wealth affects the *extensive* margin of household savings. Then, we follow Chamon and Prasad (2010) and construct a variable measuring households' savings rates to gauge the impact on the *intensive* margin of household savings. The results reveal that while preferential housing policies did not affect the incidence of saving (Table 8C, column 1), they significantly reduced the savings rates for households enjoying a rise in housing wealth (Table 8C, column 2).[27] The insignificant RD estimate regarding the incidence of savings further allows us to divide the sample into households with and without savings and explore potential heterogeneity in their consumption responses. Our results suggest that rising housing wealth significantly increases the consumption of households with savings by 34.2 % (Table 8C, column 3) but had no significant effect on those without (Table 8C, column 4), demonstrating that the diminished motive for savings is another important mechanism that drove the impact of rising housing wealth on household consumption.

To further corroborate the mechanism of a reduced savings motive, we calculate the provincial sex ratios at birth and marriage in 2005 and divide our sample into regions with high and low sex ratios according to the median value. The results (Table 8C, columns 5–8) confirm the existence of a competitive-savings motive: rising housing values alleviated more financial pressure for parents in regions with higher sex ratios, thereby boosting their consumption more than those facing less competitive marriage markets.[28]

[27] As shown in panel h of Appendix Figure A2, there is no discernible jump in the savings rate around the 90-m^2 policy cutoff before the preferential housing policies were implemented. This suggests that the decline in savings rates observed during 2010–2018 resulted from these policies, highlighting a reduced savings motive as a key channel driving the increase in household consumption.

[28] We thank an anonymous reviewer for pointing this out. To more directly examine the competitive savings motive, we first divide sampled households into subgroups based on whether they had at least one unmarried son or one unmarried daughter. To avoid potential endogenous response in fertility behavior and child gender composition, we restrict the analysis to households with children born before 2006. Reassuringly, the results (Appendix Table A4, columns 1-4) show that the estimated impact of preferential housing policies on household consumption is consistently larger for households with at least one unmarried son, regardless of the polynomial order used. Furthermore, we divide sampled households into subgroups based on whether they had only unmarried sons or only unmarried daughters. The results reported in columns 5-8 align with those in columns 5-8, indicating that the household consumption response is more pronounced for households with only sons. This finding further supports a reduced savings motive as a key channel through which housing wealth affects consumption.

Table 7
Robustness checks.

A. Alternative bandwidth	0.5 times of optimal bandwidth (1)	0.8 times of optimal bandwidth (2)	1.2 times of optimal bandwidth (3)	1.5 times of optimal bandwidth (4)
$T = 1$ [Housing size $\leq$ 90 m^2]	0.247**	0.301***	0.290***	0.272***
	(0.098)	(0.085)	(0.079)	(0.070)
Polynomial order	2	2	2	2
Optimal bandwidth	11.57	18.52	27.78	34.72
Optimal bandwidth selection method	Manual	Manual	Manual	Manual
Kernel function	Triangular	Triangular	Triangular	Triangular
Observations	7478	7478	7478	7478
B. Alternative bandwidth selection method and kernel functions	Bandwidth selection method (5)	Bandwidth selection method (6)	Kernel function: Uniform (7)	Kernel function: Epanechnikov (8)
$T = 1$ [Housing size $\leq$ 90 m^2]	0.248***	0.251***	0.265***	0.265***
	(0.072)	(0.057)	(0.086)	(0.084)
Polynomial order	2	2	2	2
Bandwidth	31.19	23.40	18.22	21.55
Bandwidth selection method	Mserd	Msetwo	Cerrd	Cerrd
Kernel function	Triangular	Triangular	Uniform	Epanechnikov
Observations	7478	7478	7478	7478
C. Alternative polynomial functions and placebo cutoffs	First-order polynomial (9)	Third-order polynomial (10)	Placebo cutoff: 80 m^2 (11)	Placebo cutoff: 100 m^2 (12)
$T = 1$ [Housing size $\leq$ 90 m^2]	0.254***	0.294***	-0.006	-0.135*
	(0.069)	(0.088)	(0.054)	(0.080)
Polynomial order	1	3	2	2
Bandwidth	16.54	26.62	15.23	24.06
Bandwidth selection method	Cerrd	Cerrd	Cerrd	Cerrd
Kernel function	Triangular	Triangular	Triangular	Triangular
Observations	7478	7478	7478	7478
D. Donut holes and alternative cluster methods	90 m^2 excluded (13)	89–91 m^2 excluded (14)	89–91 m^2 excluded (15)	Clustered at the county level (16)
$T = 1$ [Housing size $\leq$ 90 m^2]	0.293***	0.385**	0.324**	0.268***
	(0.090)	(0.159)	(0.147)	(0.096)
Polynomial order	2	2	2	2
Bandwidth	20.18	18.08	18.00	21.89
Bandwidth selection method	Cerrd	Cerrd	Cerrd	Cerrd
Kernel function	Triangular	Triangular	Uniform	Triangular
Observations	7162	7064	7064	7478

Notes: Sample = urban households with housing units purchased before 2006.All estimations are performed by local linear regressions. Regression results are bias-corrected; polynomial order =2 (expect for columns 7 and 8). Cerrd refers to coverage error rate (CER)-optimal bandwidth selector, Mserd denotes the one common mean square error (MSE)-optimal bandwidth selector, and Msetwo represents the two different MSE-optimal bandwidth selector. The dependent variable in this table is the natural logarithm of household consumption expenditure, calculated as the sum of all subcategories, each winsorized at the 98th percentile. All regressions control for predetermined variables, a dummy for multiples of 10 m^2, survey-year, home-purchase year, and county fixed effects. Standard errors in parentheses are clustered at the housing-size level. ***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1.
Data source: CFPS 2010–2018 waves.

7. Concluding remarks

China's preferential housing policies from 2006 to 2010 reduced the down payment ratio and the property deed tax rate for housing units under or equal to 90 m^2, boosting higher demands and faster housing price growth for households with (relatively) smaller units. The discontinuity structure in housing values created by these policies provides a unique opportunity to examine the causal relationship between housing wealth and household consumption.

Based on nearly representative household-level data from China, our sharp-RD analysis suggests that the consumption expenditure of urban Chinese households increased significantly due to the *unexpected* rise in housing wealth. In particular, consumption expenditures of *just-affected* households increased by 26.6 % compared to those of *just-unaffected* households, with the increase largely driven by spending on clothing, daily necessities, transportation and communication, as well as education and entertainment. Moreover, our analysis provides evidence supporting an *expectation* effect and a reduced savings motive as primary channels driving the housing-wealth effect.

Given the dominant role of housing assets in the wealth of middle-class homeowners, it is crucial to investigate how housing

Table 8A
Pure wealth effect.

	Log (household consumption expenditure)				
	Age < 45 (1)	45≤ age≤60 (2)	Age > 60 (3)	Single-unit households (4)	Multiple-unit households (5)
$T = 1$ [Housing size ≤ 90 m^2]	0.169	0.404**	0.456***	0.155*	0.436***
	(0.125)	(0.160)	(0.112)	(0.082)	(0.112)
Optimal bandwidth	21.83	19.75	22.04	27.87	18.52
Observations	1757	3015	2293	5719	1378

Notes: Sample = urban households with housing units purchased before 2006. All estimations are performed by local linear regressions. Regression results are bias-corrected; kernel = triangular; polynomial order =2; bandwidth selection method = CER-optimal bandwidth selector. The dependent variable in this table is the natural logarithm of total household consumption expenditure, calculated as the sum of all subcategories, each winsorized at the 98th percentile. All regressions control for predetermined variables, a dummy for multiples of 10 m^2, and survey-year, home-purchase year, and county fixed effects. Standard errors in parentheses are clustered at the housing-size level. ***p < 0.01, **p < 0.05, *p < 0.1. Data source: CFPS 2010–2018 waves.

Table 8B
Collateral effect.

	Whether securing a housing mortgage (1)	Consumption of households with housing montage (2)	Consumption of households without housing mortgage (3)
$T = 1$ [Housing size ≤ 90 m^2]	0.055	0.240	0.063
	(0.036)	(0.231)	(0.081)
Optimal Bandwidth	20.05	17.83	23.68
Observations	7449	664	6758

Notes: Sample = urban households with housing units purchased before 2006. All estimations are performed by local linear regressions. Regression results are bias-corrected; kernel = triangular; polynomial order =2; bandwidth selection method = CER-optimal bandwidth selector. All regressions control for predetermined variables, a dummy for multiples of 10 m^2, survey-year, home-purchase year, and county fixed effects. Standard errors in parentheses are clustered at the housing-size level. ***p < 0.01, **p < 0.05, *p < 0.1. Data source: CFPS 2010–2018 waves.

Table 8C
Reduced saving motives.

	Whether to save (1)	Saving rate (2)	Consumption of households with saving (3)	Consumption of households without saving (4)
$T = 1$ [Housing size ≤ 90 m^2]	-0.030	-0.127**	0.362***	0.030
	(0.026)	(0.054)	(0.058)	(0.130)
Optimal bandwidth	23.50	20.91	20.96	26.57
Observations	7439	5867	5323	2086
	Consumption with low sex ratio at birth (5)	Consumption with high sex ratio at birth (6)	Consumption with low sex ratio at marriage (7)	Consumption with high sex ratio at marriage (8)
$T = 1$ [Housing size ≤ 90 m^2]	0.239	0.275***	0.260***	0.347***
	(0.146)	(0.105)	(0.088)	(0.122)
Optimal bandwidth	24.78	24.88	18.04	17.97
Observations	2916	4517	4456	2964

Notes: Sample = urban households with housing units purchased before 2006. All estimations are performed by local linear regressions. Regression results are bias-corrected; kernel = triangular; polynomial order =2; bandwidth selection method = CER-optimal bandwidth selector. All regressions control for predetermined variables, a dummy for multiples of 10 m^2, and survey-year, home-purchase year, and county fixed effects. Standard errors in parentheses are clustered at the housing-size level. ***p < 0.01, **p < 0.05, *p < 0.1. Data source: CFPS 2010–2018 waves.

policies, which can generate substantial fluctuations in housing values, impact household behavior and welfare. Analyzing the same preferential housing policies (2006–2010) regarding housing size, Li et al. (2020) found a significant reduction in hours worked in response to unanticipated gains in housing wealth, suggesting that this policy portfolio may have undermined the labor market by curtailing labor-market participation. On the flip side, our paper examined another important economic outcome, household consumption, and found a significant increase in this variable resulting from the *unexpected* growth in housing wealth. While the exorbitant housing prices posed a substantial challenge for working-class homebuyers in China, the preferential housing policies (2006–2010) stimulated household consumption among the affected households. Further analysis of a broader spectrum of economic consequences is imperative to comprehensively understand the effectiveness of various regulatory housing policies in developing countries such as China.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix 1. A Two-Period Consumption Model with a Reduced Savings Motive

Here, we extend the original two-period consumption model (Section 3) to incorporate a second theoretical channel: a reduced motive for precautionary saving driven by increased housing wealth. This channel reflects the idea that households perceive their housing unit as a financial buffer for major future expenses. Consequently, a rise in housing wealth may weaken the household's incentive to maintain precautionary savings and result in higher current consumption.

Assume that a representative homeowner lives for two periods and derives utility from consumption in both periods. In addition, the household experiences disutility from maintaining precautionary saving s in the current period, which is conceptualized as a psychological cost—i.e., a precautionary motive to retain liquidity assets for future uncertainty. Crucially, this disutility is decreasing in housing wealth, which serves as a substitute for liquidity savings. The household maximizes its utility:

$$\max_{\{c_1,c_2\}} U = u(c_1) + \delta v(c_2) - \pi[P(\theta,\tau)h]s, \ \ \delta \in (0,1), \tag{A1}$$

where the sub-utility functions $u(\cdot)$ and $v(\cdot)$ are concave, satisfying $u'(\cdot) > 0, u''(\cdot) < 0, v'(\cdot) > 0$, and $v''(\cdot) < 0$. The precautionary saving motive π is a decreasing function of housing wealth, satisfying $\pi'(\cdot) < 0$. The optimization is subject to the intertemporal budget constraint:

$$c_1 + \frac{c_2}{1+r} \leq y_1 + \frac{y_2}{1+r} + \frac{P(\theta,\tau)h}{1+r}, \tag{A2}$$

which is identical to Eq. (6) in the main text since $\frac{(1+r)s}{1+r} = s$. To maximize the total utility in two periods, the budget constraint will be binding in equilibrium.

Substituting out $c_2 = (1+r)y_1 + y_2 + P(\theta,\tau)h - (1+r)c_1$ and $s = y_1 - c_1$, we reach the utility maximization condition:

$$u'(c_1) - \delta v'[(1+r)y_1 + y_2 + P(\theta,\tau)h - (1+r)c_1] + \pi[P(\theta,\tau)h] = 0. \tag{A3}$$

Applying the implicit function theorem yields:

$$\frac{dc_1}{d\theta} = \frac{\delta v'' \cdot P'(\theta,\tau)h + \pi' \cdot P'(\theta,\tau)h}{u''(c_1) + \delta(1+r)v''} < 0, \ \ \frac{dc_1}{d\tau} = \frac{\delta v'' \cdot P'(\theta,\tau)h + \pi' \cdot P'(\theta,\tau)h}{u''(c_1) + \delta(1+r)v''} < 0. \tag{A4}$$

In words, a reduced savings motive serves to raise current consumption among homeowners with housing size h when housing wealth rises.

Appendix 2. Tables and Figures

Table A1, Table A2, Table A3, Table A4.

Table A1
AIC and BIC values of different polynomial orders.

	First order	Second order	Third order	Forth order	Fifth order
AIC	17,820	17,747	17,749	17,749	17,749
BIC	17,841	17,775	17,784	17,784	17,791

Source: urban houses purchased before 2006 in CFPS.
Data source: CFPS 2010–2018 waves.

Table A2
Nonparametric RD estimates on household consumption with complete consumption data.

	Log (Household consumption expenditure) (1)	Log (Food expenditure) (2)
$T = 1$[Housing size $\leq$ 90 m^2]	0.267*** (0.082)	0.051 (0.061)
Optimal bandwidth	24.61	18.48
Observations	7046	7046
	Log (Clothing expenditure) (3)	Log (Living expenditure) (4)
$T = 1$[Housing size $\leq$ 90 m^2]	0.545** (0.213)	0.338* (0.202)
Optimal bandwidth	24.29	24.36
Observations	7046	7046
	Log (Daily good expenditure) (5)	Log (Healthcare expenditure) (6)
$T = 1$[Housing size $\leq$ 90 m^2]	0.496* (0.255)	0.005 (0.559)
Optimal bandwidth	25.72	26.09
Observations	7046	7046
	Log (Transportation & communication expenditure) (7)	Log (Education & entertainment expenditure) (8)
$T = 1$[Housing size $\leq$ 90 m^2]	0.763*** (0.175)	0.867*** (0.245)
Optimal bandwidth	20.78	19.87
Observations	7046	7046

Notes: Sample = urban households with housing units purchased before 2006. All estimations are performed by local linear regressions. Regression results are bias-corrected; kernel = triangular; polynomial order =2; bandwidth selection method = CER-optimal bandwidth selector. Each consumption subcategory is winsorized at the 98th percentile before being aggregated into total consumption. All regressions control for predetermined variables, a dummy for multiples of 10 m^2, survey-year, home-purchase year, and county fixed effects, and. Standard errors in parentheses are clustered at the housing-size level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Data source: CFPS 2010–2018 waves.

Table A3
Parametric RD estimates of housing wealth effects on household consumption.

	Log (Household consumption expenditure)			
	(1)	(2)	(3)	(4)
$T = 1$ [Housing size $\leq$ 90 m^2]	0.113**	0.131**	0.139**	0.214**
	(0.050)	(0.056)	(0.059)	(0.104)
$\widetilde{x}$	Y	Y	Y	Y
$\widetilde{x}^2$	N	Y	N	Y
$T \times \widetilde{x}$	N	N	Y	Y
$T \times \widetilde{x}^2$	N	N	N	Y
R^2	0.366	0.366	0.366	0.367
Observations	3711	3711	3711	3711

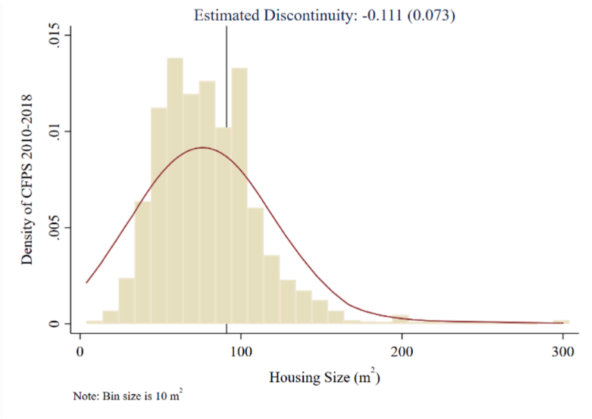
Notes: Sample = urban households with housing units purchased before 2006. The regressions are restricted to samples within the optimal bandwidth in column 1 of Table 3 derived from a nonparametric approach. The dependent variable in this table is the natural logarithm of household consumption expenditure, calculated as the sum of all subcategories, each winsorized at the 98th percentile. All regressions control for a dummy for multiples of 10 m^2, survey-year, home-purchase year, and county fixed effects. Standard errors in parentheses are clustered at the housing-size level. ***p < 0.01, **p < 0.05, *p < 0.1.
Data source: CFPS 2010–2018 waves.

Table A4
Reduced Competitive Saving Motives.

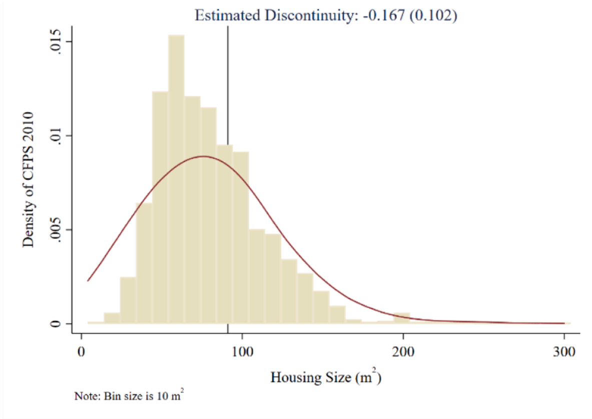
	Log (Household consumption expenditure)			
	Households with at least one unmarried son		Households with at least one unmarried daughter	
	(1)	(2)	(3)	(4)
$T = 1$[Housing size $\leq$ 90 m^2]	0.243**	0.273*	0.239	0.184
	(0.114)	(0.161)	(0.147)	(0.191)
Polynomial order	1	2	1	2
Optimal Bandwidth	13.93	17.57	12.35	22.90
Observations	2624	2624	1983	1983
	Households with only unmarried sons		Households with only unmarried daughters	
	(5)	(6)	(7)	(8)
$T = 1$[Housing size $\leq$ 90 m^2]	0.313**	0.284*	0.239	0.167
	(0.126)	(0.172)	(0.167)	(0.205)
Polynomial order	1	2	1	2
Optimal Bandwidth	13.42	18.84	12.04	26.11
Observations	2263	2263	1627	1627

Notes: Sample = urban households with housing units purchased before 2006. All estimations are performed by local linear regressions. Regression results are bias-corrected; kernel = uniform; bandwidth selection method = CER-optimal bandwidth selector. The dependent variable in this table is the natural logarithm of household consumption expenditure, calculated as the sum of all subcategories, each winsorized at the 98th percentile. All regressions control for predetermined variables, a dummy for multiples of 10 m^2, survey-year, home-purchase year, and county fixed effects. Standard errors in parentheses are clustered at the housing-size level. ***p < 0.01, **p < 0.05, *p < 0.1.
Data source: CFPS 2010–2018 waves.

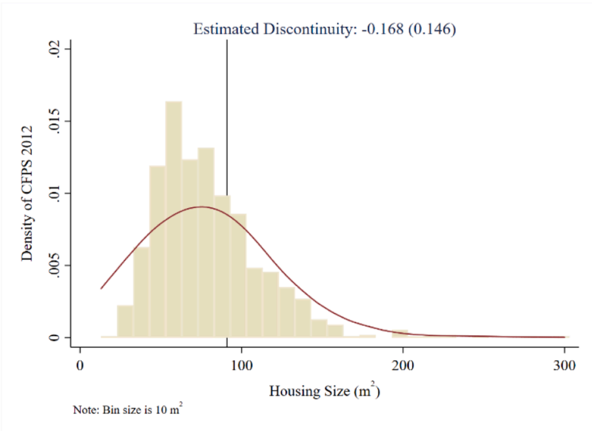
Fig. A1, Fig. A2, Fig. A3.



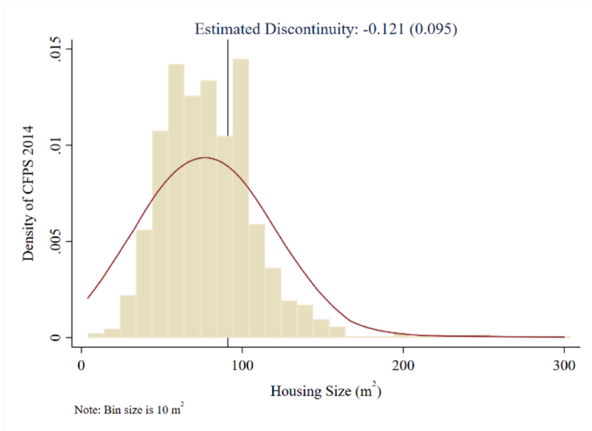
(a) CFPS (2010-2018)



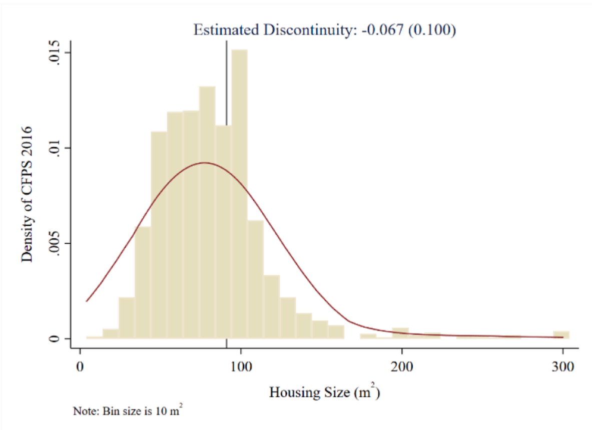
(b) CFPS 2010



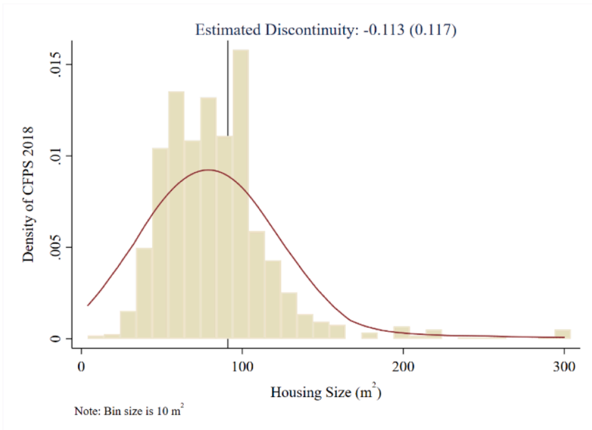
(c) CFPS 2012



(d) CFPS 2014

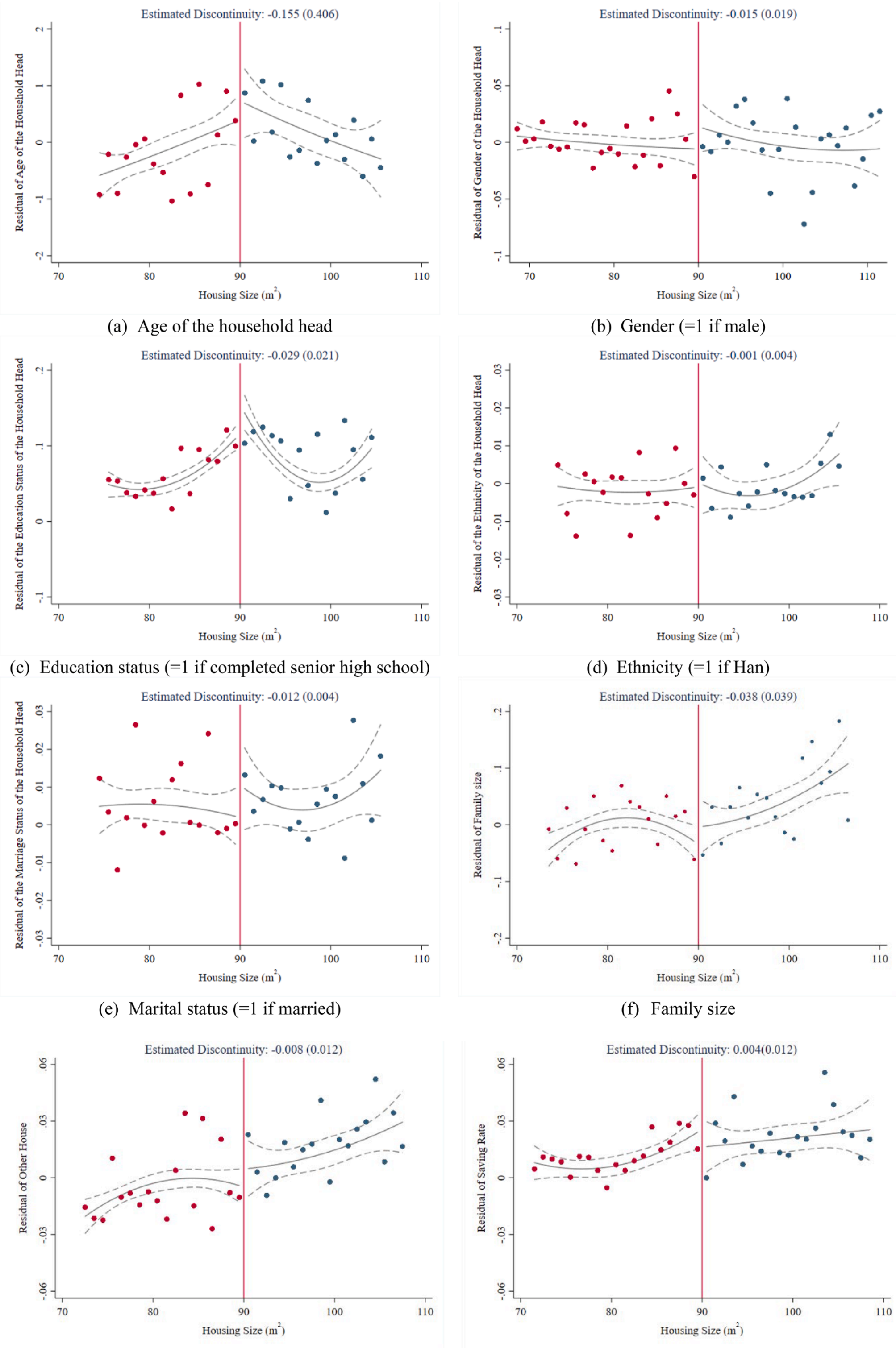


(e) CFPS 2016



(f) CFPS 2018

Fig. A1. Distribution and density tests of housing size by survey wave.
Notes: Sample = urban households with housing units purchased before 2006. Bin size = 10 m^2. Red line: the kernel density distribution (kernel = Epanechnikov). Vertical line: the cutoff point of the assignment variable (90 m^2). Data source: CFPS 2010–2018 waves.



(a) Age of the household head

(b) Gender (=1 if male)

(c) Education status (=1 if completed senior high school)

(d) Ethnicity (=1 if Han)

(e) Marital status (=1 if married)

(f) Family size

(g) Other house (=1 if had other houses)

(h) Saving rate

Fig. A2. Predetermined variables from the UHS data.

Notes: Sample = urban households. The bandwidth is calculated using the CER-optimal bandwidth selection method, and the number of bins is selected according to the ESMV method (mimicking the variance evenly-spaced method using spacing estimators). Circles represent conditional mean values of the respective variable for each bin after controlling for a dummy for multiples of 10 m^2, survey-year and county fixed effects. Solid lines: fitted values from local linear regressions with optimal bandwidths; dashed lines: 95 % confidence intervals. Vertical red line: the cutoff point of the assignment variable (90 m^2). Data source: UHS 2002–2005 waves.

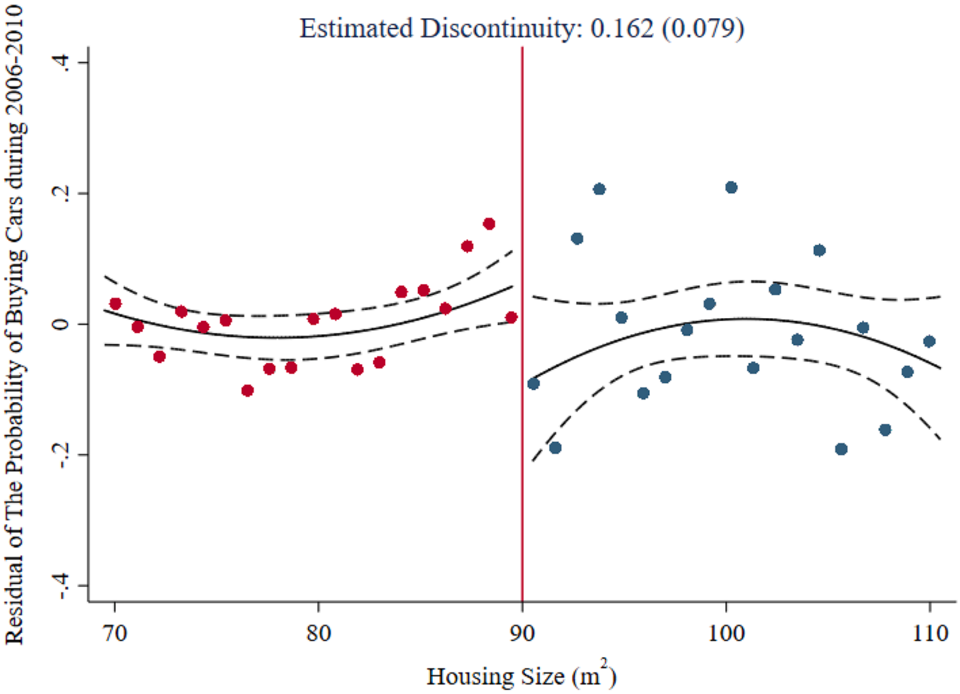


Fig. A3. Impact on the Probability of Buying Cars during 2006–2010.
Notes: Sample = urban households with housing units purchased before 2006. The bandwidth is calculated using the CER-optimal bandwidth selection method, and the number of bins is selected according to the ESMV method (mimicking the variance evenly-spaced method using spacing estimators). Circles represent mean values of the respective variable for each bin after controlling for predetermined variables, a dummy for multiples of 10 m^2, home-purchase year and county fixed effects. Solid lines: fitted values from the local linear regressions with optimal bandwidths; dashed lines: 95 % confidence intervals. Vertical line: the cutoff point of the assignment variable (90 m^2). Data source: CFPS 2010 waves.

Data availability

Data will be made available on request.

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