Under Control? Price Ceiling, Queuing, and Misallocation: Evidence from the Housing Market in China

Qiyao Zhou*

October 2023

Abstract: In this paper, I develop a model to study the equilibrium effects of price control policies. My framework considers the option for consumers to wait and re-enter the market if items are not immediately allocated due to excess demand. While waiting is common when price ceilings lead to limited supply, the cost of waiting has received limited attention in prior research. I study the housing market in Shanghai, where a price ceiling has been imposed on new houses since 2017. I have compiled a new dataset incorporating sales, characteristics of new and existing houses, and records of households' participation in housing lotteries. Using a structural model, I estimate household demand, housing supply, and waiting costs. I estimate that the price ceiling on new houses resulted in a social welfare loss of 13 billion USD from 2018 to 2020. Consumer surplus increased by 1.3 billion USD, as most of the gains from lower prices of new houses were offset by waiting costs and misallocation. Counterfactual analyses suggest that distributing a discount voucher to buyers rather than imposing a price ceiling could significantly reduce the welfare loss and achieve more equitable outcomes.

Key words: Price ceiling; waiting; misallocation; housing affordability,

*Department of Economics, University of Maryland, Tydings Hall, 7343 Preinkert Dr., College Park, MD 20742, USA. qiyaoz@umd.edu

Acknowledgements: I am indebted to Ginger Jin, Sebastian Galiani, and Maureen Cropper for their guidance and support throughout this project. I am also grateful to Milena Almagro, Ziyang Chen, Rob Clark, Paul Cheung, Maggie Hu, Mario Leccese, Sueyoul Kim, John Shea, Andrew Sweeting, Jiahao Tang, Chenyu Yang, Tong Yu, Jiangnan Zeng, as well as seminar and conference participants at University of Maryland, UEA, ASSA2023, AREUEA-AsRes for helpful comments and discussions. Of course, all errors are my own.

1 Introduction

Over the past few decades, housing expenses in many cities have risen at a pace faster than income increases (Wetzstein, 2017). This makes housing affordability a critical issue for policymakers globally. To address this crisis, price control measures, such as rent controls, have been implemented in major cities worldwide, including New York City, San Francisco, Los Angeles, and Stockholm. These policies establish upper bounds for rental prices. A large body of literature that investigates the inefficiencies of rent control, including quality degradation in rent-controlled units (Autor, Palmer, and Pathak, 2014), the conversion of rental units into condominiums reducing the supply of rental housing (Diamond, McQuade, and Qian, 2019), and triggering misallocation in the United States (Glaeser and Luttmer, 2003).

These studies of rent control focus on situations where the price increase of older units is capped, but the prices of newer units are not regulated. This paper explores price control in a different form: the prices of new houses are capped—requiring that these houses be sold by lottery—while the prices of existing houses are market driven.

This paper focuses on Shanghai, the largest city in China and the first to implement a price ceiling policy. In late 2017, Shanghai imposed price ceilings on new houses, while the prices for the existing houses remain determined by the market. The price ceiling generated excess demand, and the government used a lottery to clear this excess demand. Given this setup, households can opt to re-enter future new house lotteries, but are restricted from participating in multiple lotteries at the same time. Entering these lotteries requires depositing a downpayment for over a month without earning interest. A downpayment in Shanghai is typically over 30% of the total housing price, equivalent to 7.5 years of median households' annual salary. The deposit requirement, as well as waiting and the searching process during the lotteries incur significant costs. Shanghai's price ceiling policy has been echoed in other major Chinese cities, such as Beijing and Shenzhen, where price ceilings for new houses have similarly been implemented.

I develop a novel framework for price control policies. This framework considers consumers' option to wait and re-enter the market at a later time if items are not immediately allocated due to excess demand. While waiting is common when consumers face price ceilings, waiting costs have received limited attention in prior research.

The model endogenizes both demand and supply: On the demand side, households can choose between buying new houses with price ceilings, buying existing houses, waiting, or not buying anything. When demand exceeds supply, a lottery system decides who gets the purchasing rights for the new, price ceiling houses. Should they not succeed in the lottery, households must pay the waiting cost, and defer their purchase to a later period. Consequently, when opting to buy a new house, households are faced with a trade-off: the utility of lower prices due to the price ceiling versus the potential costs of waiting should they not win the lottery. Conversely, deciding to buy an existing house ensures households can obtain the property immediately.

On the supply side, the existing house supply is modeled as a binary choice problem, in which the current residents take the market price as given and decide whether to sell their homes. The supply of new houses is assumed to be inelastic during my sample period from 2018 to 2020, a condition established at the time developers acquire the land, typically occurring before the implementation of the price ceiling policy in the second half of 2017.

In equilibrium, two variables are endogenously determined: the probability of winning the lottery and the price of existing houses.

To estimate the model, I compile a comprehensive dataset that contains information from both the new and the existing houses. For the new houses, the data is at the apartment complex level. I can observe the price ceiling imposed by the government, the number of housing units available for the lottery, and the count of lottery participants for each apartment complex. Additionally, I can track households' lottery participation records using data sourced from the Shanghai Oriental Public Lottery Office. As for the existing house market, my data covers approximately 25% of transactions in Shanghai during my sample periods from the largest real estate agency. Each transaction record provides details about the houses' hedonic characteristics.

I specify and estimate a dynamic model to recover consumers' demand (Gowrisankaran and Rysman, 2012). Variations in the price ceiling, lottery winning probabilities, and household choice across time periods identify the households' preferences. I use each household actively participates in the market for a limited but long enough time periods, and solve the model using backward induction. To deal with unobserved quality, I instrument for price using cost-shifters and differention IV(Bayer, Ferreira, and McMillan, 2007; Calder-Wang, 2021). To deal with the endogenity in the waiting cost, I instrument it using the pre-determined and fixed new house supply. In addition, I show that introducing a stability assumption can reduce the computational burden, so that the model can be estimated under the BLP algorithm.

The demand estimation results indicate that waiting costs play a significant role in households' decision-making processes. Counterfactual analyses suggest that the price ceiling in Shanghai has a small positive effect on consumer surplus, while it reduces producer surplus significantly. The aggregate welfare loss due to the price ceiling in Shanghai from 2018 to 2020 amounts to 13.1 billion US dollars. Notably, less than 10% of the producer surplus loss translates into gains in consumer surplus. A significant portion of the consumer surplus gains, which arise from the lowered prices due to the price ceiling, is offset by waiting costs and misallocation. Waiting costs are estimated at 5.1 billion USD, constituting 39% of the welfare loss. The distributional impact of the price ceiling is also not desirable. The majority of the advantages of the price ceiling are enjoyed by house buyers of expensive residential properties. This is because the price ceiling tends to impact newer, larger, and higher-priced houses located in the city center.

One policy alternative to the price ceiling is distributing housing vouchers (Eriksen and Ross, 2015; Susin, 2002). The results reveal that distributing a 4% housing voucher to all households can achieve a similar degree of overall housing price reduction, while incurring substantially lower welfare losses – only about 0.5 billion

USD, or 4% of the losses induced by the price ceiling. This improvement comes from a significant reduction in both waiting time and misallocation. The government could fund these vouchers through a lump-sum tax levied on developers. Developers would be willing to pay this tax, as it would be less than the losses they would have incurred from the price ceiling. Distributing housing vouchers can achieve a Pareto Improvement, as it can benefit house buyers, existing home sellers, and developers alike.

To amplify the distributional impact of housing vouchers, I also investigate the effect of exclusively distributing a 6% purchase voucher to houses smaller than 90 m^2. I find that this strategy has a price reduction effect and welfare implications similar to distributing a 4% voucher to all households. However, it can be more equitable, benefiting house buyers who purchase properties valued below the 50th percentile. I have also delved into the effects of other counterfactual policies, such as increasing the supply of new houses by relaxing regulations on the floor area ratio.

This paper's contributions are three-fold. First, it contributes to the empirical literature which examines the impact of price ceilings or rent controls (Diamond, McQuade, and Qian, 2019; Mense, Michelsen, and Kholodilin, 2019; Sims, 2007) by introducing the concept of waiting costs into the analytical framework. While theoretical works have incorporated queuing into price ceilings models Glaeser (1996); Platt (2009), this is a notable gap in the empirical literature[1] Building on the recent development of structural estimation techniques (Berry, Levinsohn, and Pakes, 2004; Gowrisankaran and Rysman, 2012), this paper proposes a tractable framework to estimate consumer's demand and associated waiting costs when they face a price ceiling.The counterfactual results suggest that alternative policies, such as distributing housing vouchers, can achieve a similar effect in improving housing affordability while incurring significantly smaller welfare losses, and can achieve more equitable outcomes. The empirical framework presented in this paper could also be extended to studying price control policies in other markets, such as healthcare, where waiting

[1]The only exception is an earlier study by Deacon and Sonstelie (1985). Deacon and Sonstelie (1985) estimate a linear probability model and finds that in the 1980s, consumers' choices were influenced by waiting times at gasoline stations, where gasoline prices were controlled.

and misallocation due to price regulations are severe.

Second, this paper builds upon the growing literature regarding the design of allocation mechanisms and aligns closely with five recent studies. The first, Agarwal, Ashlagi, Rees, Somaini, and Waldinger (2021) study the patients' tradeoff between accepting a kidney and waiting for a preferable kidney. The second Waldinger (2021) and third Lee, Ferdowsian, and Yap (2022) study the allocation mechanism of public housing in the US and Singapore, respectively. The fourth, Galiani, Murphy, and Pantano (2015) examines the design of subsidies to help the residents move out of the poor neighborhood. The fifth, Li (2018) compares the social welfare implications of a lottery system and an auction system to allocate vehicle licenses, taking into account the environmental externalities. This paper investigates the allocation mechanisms in a price control problem with the option of waiting.

Third, this paper contributes to the growing body of literature examining housing market regulations in China (Agarwal, Li, Qin, Wu, and Yan, 2020; Bai, Li, and Ouyang, 2014). Alongside real estate's increasingly important role in China's economy, the government is introducing more and more regulations. This paper is the first analysis of the price ceiling in the Chinese housing market. Initially introduced in Shanghai in 2017, this policy has since been implemented in all of China's major cities. The annual sales revenue from the price-capped housing market accounted for over 10% of China's GDP in 2020.

The remainder of this paper proceeds as follows: Section 2 discusses the background of the price ceiling. Section 3 starts with a graphical example, followed by the formal model. Section 4 introduces the data and offers some descriptive evidence. Section 5 discusses the estimation and identification of the model. Section 6 presents the model estimation results. Section 7 evaluates the welfare implications of price ceiling policy and includes several counterfactual analyses. Finally, Section 8 concludes the paper.

2 Background

2.1 Housing market regulation in Shanghai

Housing prices in China have risen persistently since the 2000s. Houses in major cities like Shanghai, Beijing, and Shenzhen, are becoming less and less affordable for middle-class households. In 2016, a 90 m^2 apartment in Shanghai cost about 25 times more than the median annual household income in the city (Glaeser, Huang, Ma, and Shleifer, 2017).[2] To provide more affordable houses, the various levels of government have imposed housing regulations over the past decade.

The first wave of housing market regulation took place in 2010 and 2011. In January 2010, the Central government raised the down-payment ratio nationwide for the households' second house from 30% to 40%. This number was raised to 60% in January 2011. The mortgage rate and the transaction tax were also raised correspondingly. In addition, the Shanghai government imposed purchase restrictions in October 2010: each household could only purchase one more house after 2010. The result was that this first wave of housing market regulations between 2010 and 2011 had stabilized housing prices

Economic growth slowed beginning in 2013, and many cities, including Shanghai, loosened these restrictions in mid-2014 to boost their housing markets and local economies. This led to a subsequent rebound in housing prices.

The second wave of housing market regulation was initiated in 2016. The down-payment ratio for households' second house was raised to 70% in March 2016. At the same time, the government imposed stricter purchase restrictions. In November 2016, the down-payment ratio for a household's first house was increased from 30% to 35%. In August 2017, the government imposed a price ceiling on new houses. During our sample periods (i.e., 2018-2020), there were no significant housing policy changes in Shanghai.

[2] As a comparison, this number is around 5 in the United States.

2.2 The price ceiling in Shanghai

A price ceiling on new houses was first implemented in Shanghai in late 2016. Existing residential properties were not subject to the price ceiling, possibly due to challenges in implementation. During the implementation of the price ceiling in 2016 and early 2017, many loopholes became evident. For instance, developers conducted a lottery to clear the excess demand created by the price ceiling, and side payments to alter the lottery results were rampant. However, in August 2017, the Shanghai Oriental Lottery Public Office took charge of the lottery, effectively closing these loopholes.

In Shanghai, the government sets varying price ceilings (in *price per square meter*) for new apartment complexes. The government sets the price ceiling based on the land price when the developers purchase the land. This price ceiling information is publicized approximately one month before the lottery. Households interested in participating must submit their applications, typically a month before the lottery begins. Subsequently, developers and officials assess each household's eligibility to buy a house, since there are strict purchase restrictions in Shanghai. Additionally, households in Shanghai are not allowed to participate in two lotteries at the same time. Typically, the median interval between two lotteries spans three months.

Participating in the lottery incurs costs. Typically, households must deposit at least 30 percent of the total price at a 0% interest rate, about one month before the lottery. For households that lose the lottery, the deposit is refunded a month later. Additionally, searching for suitable apartments, filing applications, and enduring waiting periods (in the event of unfavorable lottery results) all incur time costs. As most participants in the new house lottery do not currently own a house, the cost of renting and living in (potentially) undesirable conditions for additional months in the absence of a lottery win becomes significant. Beyond these tangible costs, the process also imposes psychological costs due to its inherent uncertainty.

Shanghai enforces strict reselling and purchase constraints. According to these regulations, new houses cannot be resold until two years after the date of purchase.

If households choose to resell their houses between two to five years after purchase, they must pay an additional transaction tax of approximately 5%. Regarding purchase restrictions, households can buy an apartment in Shanghai if they possess a Shanghai hukou (household registration) or have paid social security tax in Shanghai for over five consecutive years, and if they own fewer than two properties in Shanghai. There are more stringent policies for unmarried individuals. These regulations apply to both new and existing apartments. These constraints discourage arbitrage in the new home market. Consequently, typical house buyers are young households without houses in Shanghai. This study does not consider the arbitragers' utility separately.

3 Model

In this section, I will begin by providing a graphical example to illustrate the economic trade-offs and intuitions of the price ceiling model with waiting. Following that, I will present a formal model that characterizes the equilibrium concepts.

3.1 Graphical example

This section serves two purposes. Firstly, it provides an illustrative example that underscores the significance of the waiting period in the context of a price ceiling. Secondly, it compares the model presented in this paper, which incorporates waiting costs, to classic price ceiling models. To facilitate a straightforward exposition, I simplify the analysis by assuming linear demand, supply, and a homogeneous waiting cost.

The key distinction between the price ceiling model presented in this paper and the classic models found in textbook analyses is the incorporation of waiting in the model. In the price ceiling model accounting for waiting costs, consumers have the option to wait, a decision that incurs a waiting cost. If consumers are unable to acquire the good in the present due to the excess demand resulting from the price ceiling, they have the choice to pay the waiting cost and engage in the market at a later time. Therefore, when consumers are making their purchase decisions, they will internalize the expected waiting cost in their indirect utility function.

In this example, to align with our empirical analyses, we consider the scenario in which the prices of new houses are capped, while the prices of existing houses are market-driven.

3.1.1 Classic price ceiling model without waiting

We begin with the classic (second-generation) price ceiling model depicted in the literature (McDonald and McMillen, 2010; Mense, Michelsen, and Kholodilin, 2019) — as illustrated in Figure 1 — which eliminates the potential for future participation and the option to wait once households are unsuccessful in the initial lottery.[3]

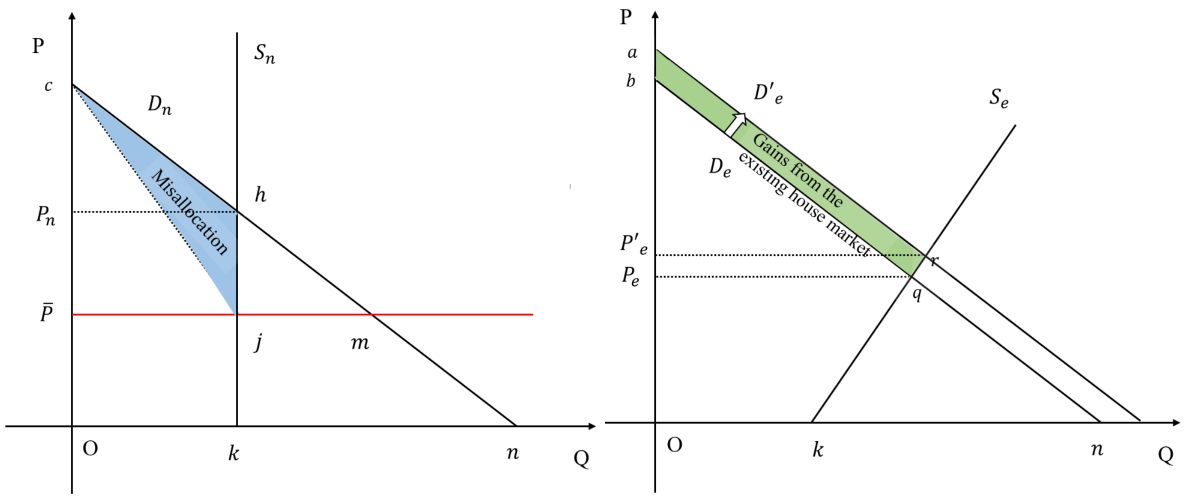
In the new house market (Panel (a)), the supply of the new house is assumed to be fixed at S_n. Note that an elastic new house supply curve will not change the results. The demand curve for new houses is denoted by D_n. P_n denotes the equilibrium new house price when there is no price ceiling. When a binding price ceiling is implemented at $\bar{P}$, the resulting excess demand is represented by the line jm. In the event that the government uses a lottery to clear the market, the consumer surplus is represented by the region $c\bar{P}j$. Conversely, in the first-best allocation mechanism (with the price ceiling), the government can allocate the good based on the consumers' willingness to pay, and the resulting consumer surplus is represented by the region $c\bar{P}jh$. The triangle cjh shaded in blue represents the misallocation that arises due to the random assignment of the good.

Panel (b) shows the impact of the price ceiling on the unregulated market (existing house market). D_e, S_e, and P_e correspond to the demand curve for existing houses, the supply curve for existing houses, and the equilibrium price, respectively. McDonald and McMillen (2010); Mense, Michelsen, and Kholodilin (2019) assume a one-period, static model. In their model, since new and existing houses are substi-

[3]The term "second generation" indicates the presence of houses in the model exempt from the price ceiling.

tutes, households who lose the lottery in the new house market will switch to the existing house market. As a result, the existing house demand curve will move from D_e to D'_e. Correspondingly, the existing house price will increase from P_e to P'_e. The region *abrq* represents the welfare gains from the existing house market. The total welfare losses due to the price ceiling in the new and existing house markets would be $cjh - abrq$.

Figure 1: Figure of the classic price ceiling model



(a) New house market

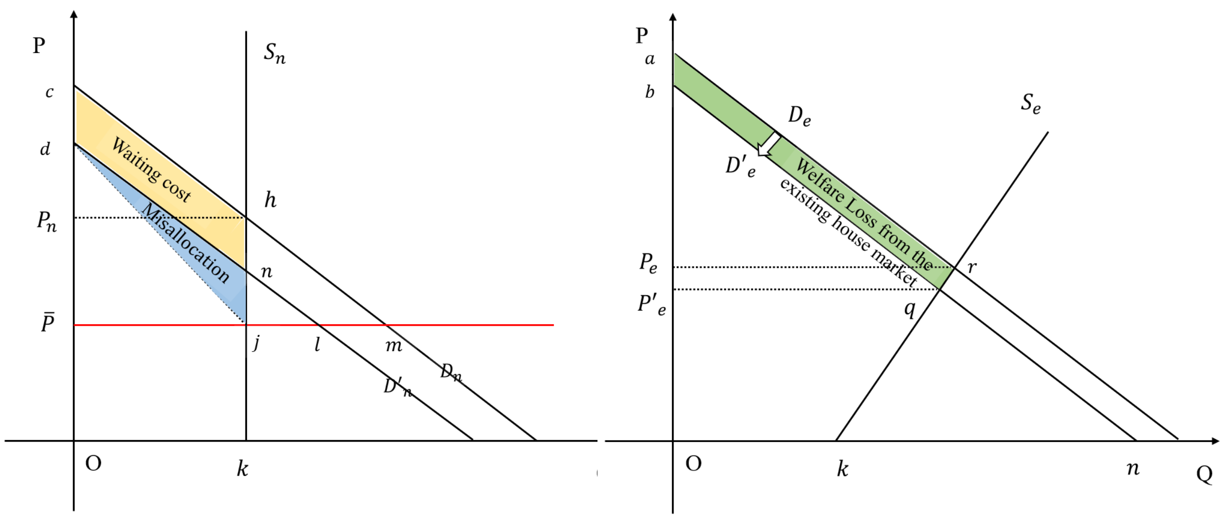
(b) Exsiting house market

3.1.2 Price ceiling model with waiting

Now in Figure 2, let's examine the price ceiling model with waiting, maintaining the same notations used in Figure 1. In the price ceiling model with waiting, if households are unable to acquire the good in the present due to the excess demand resulting from the price ceiling, they have the choice to pay the waiting cost and engage in the market at a later time. Households can incorporate the expected waiting cost into their indirect utility function. The inclusion of waiting shifts the demand curve downward from D_n to D'_n. As will become clear in the later part of the model, the expected waiting cost can be expressed as a function of lottery winning probability. A more competitive lottery implies a longer waiting time and higher costs.In Panel (a), Figure 2, the area *cdnh* represents the waiting costs associated with the price ceiling (marked in yellow).

The inclusion of dynamics and waiting costs in the model also alters the region of misallocation and the spillover effect in the existing house market. As seen in Panel (a) of Figure 2, the excess demand is reduced from jm to jl after the inclusion of waiting costs. Households in lm who have a lower willingness to pay for houses are sorted out due to the waiting costs. Consequently, the welfare losses stemming from misallocation are reduced to the region djn compared to the model without waiting, as depicted in Figure 1 (a). The waiting to sorting story emerges because only households with a high willingness to pay will choose to remain in the waiting line and pay the waiting cost.

Figure 2: Figure of the price ceiling model with waiting



(a) New house market

(b) Exsiting house market

Panel (b) shows the impact of the price ceiling on the unregulated market (existing house market). Even though households have to queue and wait for new houses, lower prices due to the price ceiling makes the new houses more appealing. And households that lose the new house lottery can still participate in it in the future. Consequently, some of the households that initially opted to buy existing houses when there was no price ceiling switch to the queuing line for new houses, driving down the demand curve for existing houses from D_e to D'_e. The total welfare losses in the price ceiling model with waiting becomes $djn + cdnh + abrq$.

In summary, the inclusion of waiting in the price ceiling model generates waiting costs. However, this waiting cost can also reduce misallocation through the waiting-to-sorting channel. The demand and price for existing houses will also decrease because households who initially chose to purchase existing houses are attracted to join the waiting line for new houses due to the lower prices.

In the next sections, I will provide a formal model to characterize the equilibrium of the price ceiling with waiting. This model will also guide the empirical estimation.

3.2 Demand

3.2.1 Consumer choice

In each period, household i chooses among three options: (1) purchasing a new house (N); (2) purchasing an existing house (E); (3) waiting until the next period (W) to participate.

Household i's indirect utility function of *successfully* purchasing a new house project j in time t:

$$u_{ij} = x_j \beta_i - \alpha_i \bar{p}_j + \xi_j + \epsilon_{ij} \tag{1}$$

Where $\bar{p}_j$ denotes the price ceiling set on house j, x_j denotes house j's observable characteristics, and ξ_j includes j's unobservable characteristics. I assume that the error term ϵ_{ij} follows a type 1 extreme value distribution. If household i is unsuccessful (F) at winning the new house lottery in time t or chooses to wait (W), she pays a time-invariant waiting cost c_i and continues to the next period $t+1$:

$$U_{i,t}(W) = U_{ij,t}(F) = -c_i + V_{i,t+1} \tag{2}$$

Following Glaeser (1996), for simplicity, I assume the waiting cost c_i accounts for the utility loss from discounting. If household i chooses to purchase an existing house product (j'), she will get the house immediately, and her utility is:

$$U_{ij',t}(E) = x_{j',t}\beta_i - \alpha_i p_{j',t} + \xi_{j',t} + \epsilon_{ij',t} \tag{3}$$

Therefore, in each period, household i selects among a new house project j (N), an existing house project j' (E), waiting (W), and the outside option to maximize her expected utility:

$$V_{i,t} = max\left[v_{ij,t}(N); v_{ij',t}(E); v_{i,t}(W); 0\right] \tag{4}$$

Denote $Pr_{j,t}$ as the lottery winning probability of the new house project j. We have:

$$\begin{aligned} v_{ij,t}(N) &= Pr_{j,t}U_{ij,t} + (1 - Pr_{j,t})U_{i,t}(W) \\ v_{ij',t}(E) &= U_{ij',t}(E) \\ v_{i,t}(W) &= U_{i,t}(W) \end{aligned} \tag{5}$$

Plugging Equation (2) into Equation (5), we have:

$$v_{ij,t}(N) = Pr_{j,t}U_{ij,t} + (1 - Pr_{j,t})(-c + V_{i,t+1}) \tag{6}$$

Define $\Delta_{i,t+1} = V_{i,t+1} - V_{i,t}$. When household i chooses new house project j in time t (i.e., $v_{ij,t}(N) = V_{i,t}$), Equation (6) can be rewritten as:

$$\begin{aligned} v_{ij,t}(N) &= Pr_{j,t}U_{ij,t} + (1 - Pr_{j,t})(-c + v_{ij,t}(N) + \Delta_{i,t}) \\ v_{ij,t}(N) &= U_{ij,t} - \frac{1 - Pr_{j,t}}{Pr_{j,t}}c_i + \frac{1 - Pr_{j,t}}{Pr_{j,t}}\Delta_{i,t+1} \end{aligned} \tag{7}$$

3.2.2 Stability assumption

Before proceeding, let's first discuss the stability assumption, which can greatly simplify the demand model and estimation.

Stability assumption: Household i's valuation of being in the market today is the same as her valuation of being in the market tomorrow. More formally: $\Delta_{i,t+1} = 0$.

Note that this stability assumption is a weaker version of the assumption in Caetano (2019), where he assumes that all product's expected characteristics remain the same all the time in a dynamic neighborhood choice model. There are some reasons why one might argue that the stability assumption may not be strong in the context of this paper. First, it is worth noting that the stability is required with respect to the expectations of the households, not with respect to reality. Second, the time span covered in this paper ranges from 2018 to 2020, which is relatively short. Thus, the space of time for which stability is required is rather small. Finally, in the empirical setting, I will show the results under a dynamic model where the stability assumption is relaxed, but at the cost of high computational burden.

Under the stability assumption, Equation (6) can be re-written as:

$$v_{ij,t}(N) = U_{ij,t} - \frac{1 - Pr_{j,t}}{Pr_{j,t}} c$$

The waiting cost c enters directly into the households' indirect utility function. The structural parameter $\frac{1-Pr_{j,new,t}}{Pr_{j,new,t}}\, c_i$ has reduced-form interpretation: household i needs to pay a higher waiting cost if the new house lottery is competitive (i.e., $Pr_{j,new,t}$ is low).

For more intuitive interpretation of the term $\frac{1-Pr_{j,t}}{Pr_{j,t}} c$, consider a stronger version of the stability assumption. In this scenario, the same bundle of price and characteristics $(p_{j,old}, x_{j,old}, p_{j,new}, x_{j,new})$ is available in the market at all times, with household i consistently opting for the same choice. Assuming a new house j has a 10% lottery winning probability at time t, the term $\frac{1-Pr_{j,new,t}}{Pr_{j,new,t}}\, c_i$ equals $9c_i$. This implies that household i would have to enter the lottery ten times, incurring waiting costs over nine periods, to stand a chance of winning the new house j's lottery.

The indirect utility function u_{ij} for both new and existing houses under the stability assumption can be written as:

$$u_{ij} = x_j \beta_i - \alpha_i p_j + \xi_j - \frac{1 - Pr_{j,t}}{Pr_{j,t}} c_i + \epsilon_{ij} \tag{8}$$

Note that for all existing houses, Where $Pr_{j,t} = 1$, and the waiting cost term $\frac{1-Pr_{j,t}}{Pr_{j,t}} c_i = 0$.

3.2.3 Market shares

Household i's choice probability of the houses can be written as:

$$s_{ij,t} = \frac{exp(v_{ij,t})}{1 + \sum_{j,old} exp(v_{ij',t}(E)) + \sum_{j,new} exp(v_{ij,t}(N)) + exp(v_{i,t}(W))} \tag{9}$$

The aggregate market share of type j house is obtained by aggregating over consumers' characteristics:

$$s_{j,t} = \int \int \int s_{ij,t} dG(\alpha_i, c_i, \beta_i) \tag{10}$$

The probability of winning the new house lottery $Pr_{j,new}$ is also determined in equilibrium.

$$Pr_{j,new} = \frac{\bar{K}_j}{N * s_j} \tag{11}$$

Where N denotes the market size, and $\bar{K}_j$ is the supply of the new house j, which is assumed to be predetermined in my empirical context.[4]

3.3 Supply

3.3.1 Supply of new houses

In the model, the supply of new houses is considered to be predetermined ($\bar{K}_j$). The construction process for a project usually spans three to four years. For the majority of the projects analyzed in this paper during the sample period (2018-2020), construction plans were established prior to the implementation of the price ceiling. The long-term supply of new houses in China also tends to be inelastic, since the government controls the supply of residential land.

[4] See the supply section for a detailed discussion.

3.3.2 Supply of existing houses

The supply of existing houses by current residents is modeled as a binary choice problem where the current residents take the price as given and decide whether to sell the house or not. The owner exits the market once she has sold her houses. Specifically, if seller s sells her houses, her indirect utility is:

$$u_{s,1jt} = \alpha_s p_{jt} + \xi_{s,1jt} + \epsilon_{s,1jt} \tag{12}$$

Where $-\xi_{s,jt} - \epsilon_{s,jt}$ is the reservation utility for seller s. I ignore the bargaining process between the seller and the buyer.

If the seller chooses not to sell, she has the option to sell her houses in the next time period. Her indirect utility becomes:

$$u_{s,0jt} = \mathbb{E}V_{s,jt+1} + \xi_{s,0jt} + \epsilon_{s,0jt} \tag{13}$$

Suppose that $\epsilon_{s,1jt}$ and $\epsilon_{s,0jt}$ are identically and independently distributed following a type 1 extreme value distribution. Seller s's continuation value has the following form:

$$\mathbb{E}V_{s,jt+1} = \gamma + ln(exp(\bar{u_{0jt}}) + \exp(\bar{u_{1jt}})) \tag{14}$$

Where $\bar{u_{0jt}}$ and $\bar{u_{0jt}}$ denote the mean utility level, and γ is an Euler constant. The market share for type j house at t can be written as:

$$s_{1jt} = \frac{\bar{u_{1jt}}}{\bar{u_{0jt}} + \bar{u_{1jt}}} \tag{15}$$

3.4 Equilibrium

I now define the *price ceiling equilibrium* in the steady state. There are two endogenous variables determined in the equilibrium in the model: **the price of the existing houses** and **the lottery winning probability**.

In the new house market, the number of lottery participants equals the (predetermined) supply of the new houses plus the equilibrium queuing line.

$$\forall j, new: \ D_j(\bar{p}_j, Pr_{j,new}, p_{-j}, Pr_{-j}) = \bar{K}_j + N_j(\bar{p}_j, Pr_{j,new}, p_{-j}, Pr_{-j}) \tag{16}$$

The lottery winning probability $Pr_{j,new}$ is determined in equation (11), so the queuing line N_j can be written as:

$$N_j = \frac{\bar{K}_j}{Pr_{j,new}} - \bar{K}_j \tag{17}$$

In the existing house market, the supply of the existing houses equals the demand:

$$\forall j, old: \ D_j(p_j, p_{-j}, Pr_{-j}) = s_j(p_j) \tag{18}$$

When we impose the stability assumption, we also need a steady-state market balance condition. It can be written as follows:

$$\forall j, t: \ \Gamma_t = \sum_j \bar{K}_{jt} \tag{19}$$

Where Γ_t denotes the arrival of new consumers who choose to purchase new houses in time t. Equation (19) states that in the steady state, the arrival of new consumers equals the total supply of the new houses.

The steady-state market balance condition ensures that the length of the queuing line remains stable. This prevents the equilibrium waiting line in the steady state from continuously increasing or decreasing.

In Section 5, I will discuss the estimation steps for both the dynamic model and the model under stability assumptions, along with the instruments I use. The key parameters to be identified are the price coefficients for house buyers (β_i) and existing house sellers (α_s), as well as the waiting cost (c_i) for house buyers.

4 Data

4.1 New house data

Data on the price ceiling, the supply of new houses, and the number of new house lottery participants information come from the CRIC (China Real Estate Information Center) dataset and official documents. I supplement the new houses' hedonic characteristics (i.e., number of bedrooms, bathrooms, livingrooms, kitchens, and total area) with Lianjia's apartment complex dataset. The new house data is at the apartment complex/project level (i.e., I treat the apartments within an apartment complex as homogeneous). There are a total of 484 new apartment complexes observed from 2018 to 2020.[5] Due to the strict purchase and resale limitations in Shanghai, instances of speculation in new properties are rare. For instance, among the roughly 90,000 new houses that were sold in 2018 and 2019 (subject to price ceilings and eligible for resale in 2021), only 161 were found on the Lianjia platform in 2021. It should be noted that this paper does not explicitly specify or estimate the utility function of speculators.

4.2 Lottery participants' data

The lottery participation information comes from the Shanghai Oriental Public Lottery Office. This dataset contains a unique identification code that matches the buyers across lotteries. It also contains information about buyers' hukou (city of permanent residence), gender, and whether they won the lottery.

[5]Note that I exclude the new apartment complexes in ChongMing district, an isolated island in the northeast part of Shanghai. I also exclude the commercial-residential mixed-use properties and single-family houses (villas).

4.3 Existing house data

Shanghai's existing house transaction data comes from Lianjia, the largest online real estate agency in China. This dataset contains 130,505 transaction records from 2018 to 2020, representing approximately 25% of the existing house market in Shanghai. Each observation includes information on the properties' hedonic attributes, such as the number of bedrooms, bathrooms, living rooms, kitchens, and total area, along with transaction information, such as the listing and sale prices and dates, as well as the buyers' search histroy, including the number of link clicks.

I also obtain aggregate-level data on existing house transactions from the CRIC dataset, which provides aggregate information on the number of transactions by district and month. To construct the complete existing house transaction data, I combine the micro-level transaction records with the aggregate-level information. I scale the micro-level observations in Lianjia by a factor of $\frac{1}{k_{it}}$, where k_{it} denotes Lianjia's market share in district i, quarter t. It is possible that the market share for certain types of houses sold on the Lianjia platform may not be representative. To address this concern, I control for town/subdistrict by house type fixed effects.[6]

4.4 Summary statistics

Table 1 reports the summary statistics of the main variables for both new and existing houses. On average, new houses are larger and more expensive than the existing ones. *demand* and *supply* in Panel A refer to the number of lottery participants, and the number of houses in an apartment complex that are available for the lottery, respectively. The mean of the lottery winning probability is around 50%. A total of 187 apartment complexes face a binding price ceiling during our sample periods (i.e.,2018 to 2020). For the apartment complexes that do not face a binding price ceiling, potential buyers' waiting costs equal zero.

Figure 3, Panel (a) displays the spatial distribution of lottery winning probabil-

[6] The definition of the product is discussed in section 6.1.

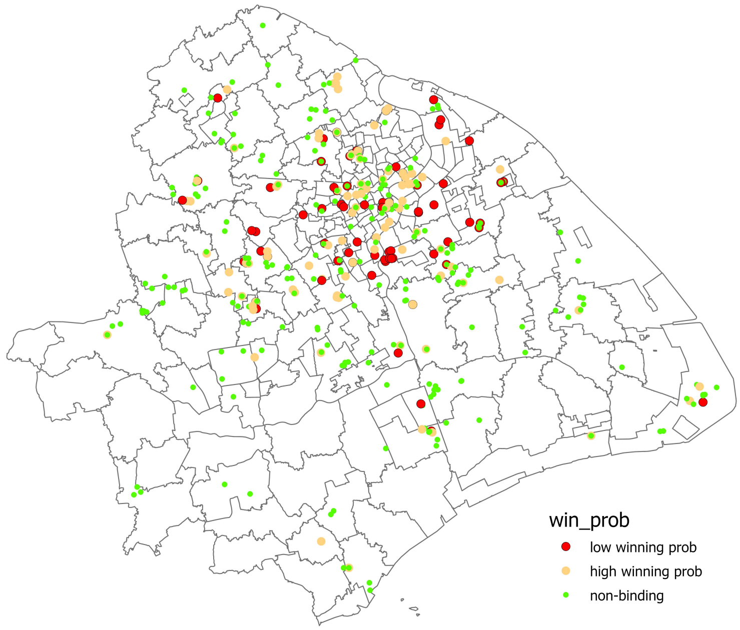
ity, with stricter price ceilings observed in the downtown compared to the suburban areas. Meanwhile, Panel (b) of Figure 3 illustrates the spatial distribution of existing house prices in Shanghai, which aligns with our expectations, as properties in downtown tend to be more expensive than those in suburbans.

Table 1: Summary statistics

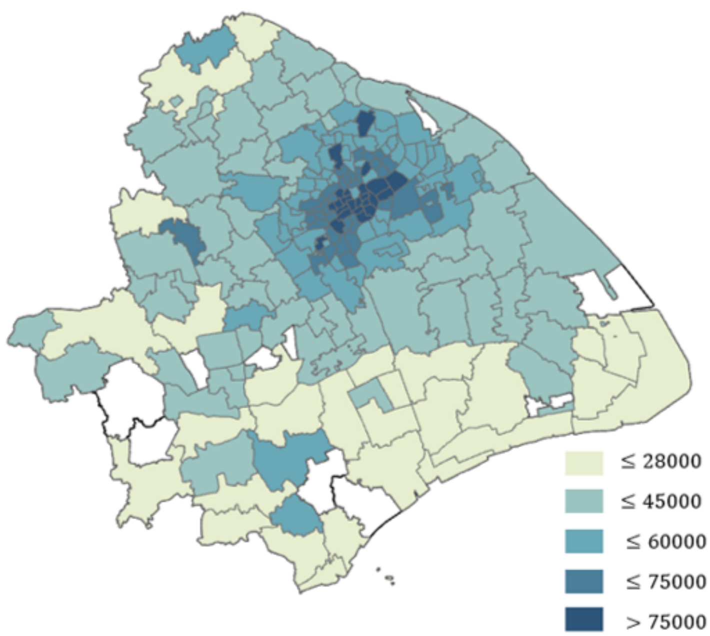
	Obs	Mean	Std.	P25	P75
Panel A: new houses (apartment complex level)					
Price per sq meter	484	62781	30872	39039	85611
Demand (# of lottery participants)	486	310	418	74	366
Supply ((# of houses available for lottery)	486	289	184	150	367
Win probability (binding P.C.)	187	0.58	0.27	0.36	0.77
Area	486	128.3	54.1	95	138
Bedroom	486	3.1	0.7	3	3
Livingroom	486	1.0	0.2	1	1
Bathroom	486	2.1	0.9	2	2
Kitchen	486	1.0	0.1	1	1
Distance to CBD (km)	486	22.0	13.80	10.6	31.1
Panel A: existing houses					
Price per sq meter (yuan)	116145	51506	20526	37216	61898
Area	116145	76.5	40.7	51.6	89.9
Bedroom	116107	2.2	1.4	1	3
livingroom	116107	1.7	1.5	1	2
bathroom	116107	1.2	0.5	1	1
kitchen	116107	0.97	0.20	1	1
age	111888	19.9	10.4	12	26
Distance to CBD (km)	116145	15.8	10.0	8.6	20.2

Notes: (1) New house data in Panel A is at the apartment complex level, the existing house data is at the transaction level. I exclude the houses transacted in the Chongming district, which is the island in the northeast part of Shanghai.

Figure 3: Housing market in Shanghai: 2018-2020



(a) Winning probability of the new residential properties



(b) Average price of the existing residential properties

4.5 Descriptive evidence

4.5.1 Hedonic regression results

I estimate the hedonic price equation (20) for both new and existing houses in Shanghai. The dependent variable lnp_i is the logarithm of the price per square meters of house i. $distcbd_i$ denotes house i's distance to the CBD. X_i is a vector of house i's characteristics, including area, the number of bedrooms, bathrooms, livingrooms, kitchens, and the age of the house. μ_i is a vector of fixed effects. The estimation results are presented in Table 2. Columns (1) and (2) show results using the existing home transaction data, whereas Column (3) reports the results from new home data aggregated at the apartment complex level.

$$lnp_i = \beta_0 + \beta_1(distcbd_i) + \beta_2(X_i) + \mu_i + \epsilon_i \tag{20}$$

The results in Table 2 indicate a significant difference in the estimated price gradient between new and existing houses. For existing houses, the price-distance gradient is approximately 0.03, while for new homes, it reduces to around 0.012. This disparity in the price-distance gradient provides suggestive evidence that a price ceiling may be distorting market prices. This trend aligns with the findings in Panel (a) of Figure 3, where downtown apartment complexes are subject to stricter price ceilings compared to those in suburban areas.

4.5.2 Lottery winning probability and waiting time

A key theoretical prediction of the model is that the probability of winning the lottery is strongly correlated with households' waiting time. Consequently, entering a lottery with a low probability of winning has a longer expected waiting time. Figure 4 presents the relationship between the probability of winning the lottery and the waiting time of participants. The data is aggregated at the apartment complex level, with the y-axis representing the average waiting time of participants in each new house project, and x-axis representing the lottery winning probability. Figure 4 reveals a distinct declining relationship between the probability of winning the

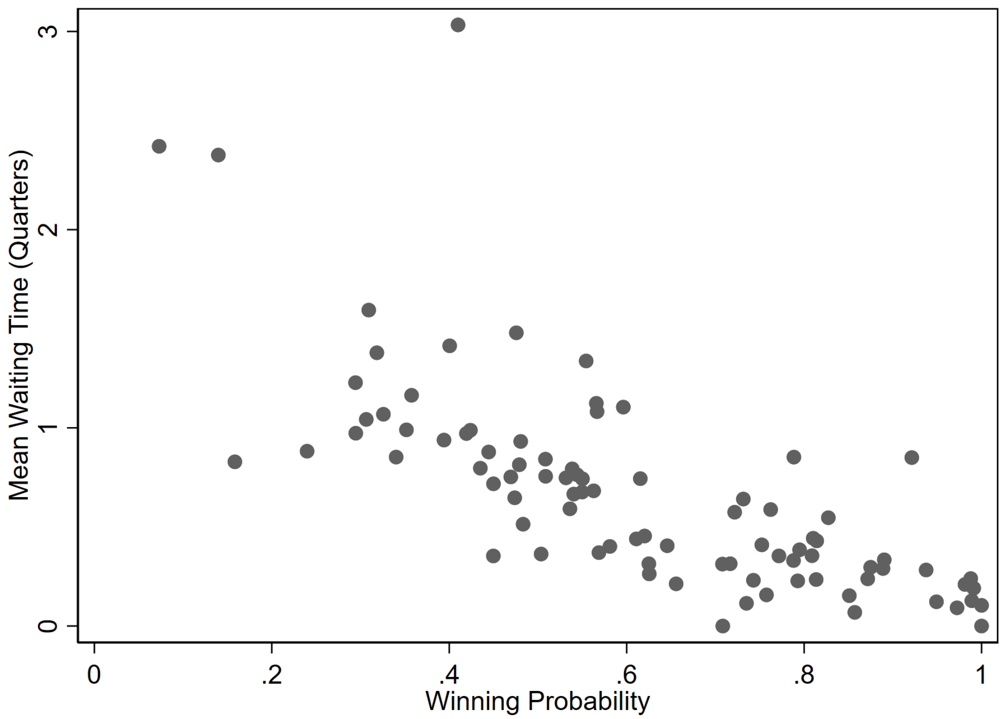
Table 2: Hedonic regression results

	(1)	(2)	(3)
Dep var	ln (prices per sq meter)		
	existing houses		new house
Distance to CBD (km)	**-0.0271*** **	**-0.0319*** **	**-0.0125***
	(0.0001)	**(0.0005)**	**(0.0072)**
bedroom	-0.0032***	-0.0027***	-0.0435*
	(0.0007)	(0.0006)	(0.0228)
livingroom	0.0056***	0.0038***	-0.0868
	(0.0005)	(0.0005)	(0.072)
bathroom	0.091***	0.053***	0.0646***
	(0.0029)	(0.0022)	(0.0188)
kitchen	0.008*	0.006*	-0.0648
	(0.004)	(0.0032)	(0.0639)
area (100 m^2)	-0.011***	-0.027***	0.107***
	(0.004)	(0.003)	(0.036)
age	0.0058***	-0.0019***	
	(0.0001)	(0.0001)	
elevator	0.155***	0.081***	
	(0.002)	(0.002)	
2019.deal_year	-0.034***	-0.038***	0.0621***
	(0.002)	(0.002)	(0.023)
2020.deal_year	0.026***	0.0145***	0.0875***
	(0.002)	(0.002)	(0.024)
Subdistrict F.E.		X	X
Observations	110993	110993	484
R-squared	0.531	0.715	0.893

Notes: (1) 2018 is the base year, with its coefficients being absorbed. (2) Standard errors in parenthesis, *** p<0.01, ** p<0.05, * p<0.1.

new house lottery and the participants' waiting time, corroborating our theoretical predictions.

Figure 4: Lottery winning probability and waiting time



Notes: (1)Each dot represents an apartment complex. (2) The y-axis represents the mean waiting time for households that participated in the lottery. (3) I do not have lottery participation records after 2020. Consequently, I cannot observe the waiting patterns of households that lost the lottery in 2020. Thus, the sample period for this data is restricted to new houses with lotteries held in 2018 and 2019. (4)Due to the short sample period, there still exists potential underestimation of waiting times, especially for houses with a low probability of winning the lottery.

5 Estimation

This section discusses the estimation strategies I employed in this paper. I first define a housing "product". Then I discuss the details in demand and supply estimation.

5.1 The definition of a product

I define each new apartment complex as a distinct product. The product space for existing houses in this paper is defined at the town/subdistrict level (similar to a zipcode) by house type. There are a total of 214 towns/subdistricts in Shanghai. In downtown Shanghai, a representative town/subdistrict encompasses around 100,000 residents within a 4-square-kilometer area. Existing houses within each town/subdistrict are divided into three types based on their construction area: (1) Small types are houses with a construction area smaller than $60m^2$. They typically have only one bedroom and one bathroom. These houses account for around 35% of transactions in the sample, (2) Medium types are houses with a construction area between $60m^2$ and $90m^2$. They typically have two bedrooms and two bathrooms. These houses account for around 40% of transactions in the sample. (3) Large types are houses with a construction area larger than $90m^2$. They typically have three bedrooms and two bathrooms. These houses make up the remaining 25% of transactions in the sample. There are a total of 484 new house products and 562 old house products in my sample. The market is defined at the quarter level.

5.2 Demand estimation

I first discuss the demand estimation for the dynamic model without imposing the assumption: $\Delta_{it} = 0$. I then discuss the model estimation under the stability assumption. Finally, I present the choice of the instruments.

5.2.1 The flexible demand model

I estimate the demand for houses using the generalized method of moments. The estimation algorithm follows from Lee, Ferdowsian, and Yap (2022) and is akin to the nested fixed point algorithm in Berry, Levinsohn, and Pakes (1995).

I assume that potential house buyers are perfect foresight and they can participate in the market for at most 6 time periods (i.e., 6 quarters). In other words, if they cannot get a house within 6 time periods, they will exit the market. The 6 time periods assumption is mainly for the tractability of the estimation of the model, and is likely innocuous since in the data more than 95% of the households win a new house lottery within 4 quarters.

The estimation algorithm can be decomposed into three loops:

Inner loop: Given a guess of the parameters, the observed market share, price, and housing characteristics, I solve the dynamic program of each type of household using backward induction, and obtain the model-predicted choice probability.

Middle loop: This loop is akin to the inner loop in Berry, Levinsohn, and Pakes (1995). I use the contraction mapping algorithm to find the mean utility parameters that equate the observed market shares to the model predicted market shares. I then find the model parameters using the instruments that will be discussed in section 5.2.3. Next, I form an objective function based on the model residuals.

Outer loop: This loop is akin to the outer loop in Berry, Levinsohn, and Pakes (1995). I search over nonlinear parameters that minimize the criterion function formed in the middle loop.

5.2.2 Demand estimation under the stability assumption

Equation (8) demonstrates that, after assuming that household valuations in the steady state remain consistent over time (i.e., the stability assumption), the indirect utility function for house buyers can be simplified. The model's estimation follows the standard algorithm by Berry, Levinsohn, and Pakes (1995). The $\frac{1-Pr_{j,t}}{Pr_{j,t}}$, which measures waiting, is treated as a variable to be included in the household's indirect utility function. Since the lottery winning probability $Pr_{j,t}$ is endogenously determined in the equilibrium, we need to find an instrument for it. I will discuss the instrumental variables I use in the next subsection.

5.2.3 Demand instruments

The price ceiling for new houses $\bar{p}_{j,new}$ may be endogenous. It is plausible that the government could establish a higher price ceiling for apartment complexes with superior location and construction quality. To serve as an instrument for $\bar{p}_{j,new}$, I employ the cost shifter, specifically the land price per square meter at the time the developer acquired the land. Policy documents, along with Shanghai's statistical yearbook, assert that the price ceilings are set in accordance with land prices—a relationship they refer to as a "linkage" between housing price and land price. To account for the influence of location, town or subdistrict fixed effects are included in the model. This concept is similar to matching, given that the area of a subdistrict located in downtown has an area of approximately 4 square kilometers (analogous to sketching a circle with a radius of 1km). This method aligns with the approach Chen and Kung (2019) used for handling endogeneity concerns in land quality, where radii of 0.5 km and 1.5 km were applied. Conditional on the subdistrict/town fixed effects, land prices are unlikely to affect a building's construction quality, since the price of land is a sunk cost.

Similar to the findings of Bayer, Ferreira, and McMillan (2007) and Calder-Wang (2021), the number of listings of existing houses in adjacent towns/subdistricts with similar characteristics is used as the instrument for the price of the existing houses. The intuition is that houses situated in a crowded part of the housing attribute space have a low equilibrium price, regardless of their own unobserved quality.

The lottery winning probability $Pr_{j,new}$ is also endogenous. This is because, by its definition, it is directly influenced by the demand (s_j), i.e., $Pr_{j,new} = \frac{\bar{K}_j}{s_j}$. The supply of new houses $\bar{K}_j$ is used as the instrument for Pr_j. $\bar{K}_j$ is a predetermined variable and strongly correlates with Pr_j.

5.3 Supply of existing houses

To estimate the supply of existing houses, I utilize the approach employed in Arcidiacono and Miller (2011); Lee, Ferdowsian, and Yap (2022), which leverages the fact that selling an existing house represents a concluding decision, allowing the dynamic problem to be simplified into a static one.

Taking logarithm of equation(15), we have:

$$ln(s_{1jt}) - ln(s_{0jt}) = \bar{u_{1jt}} - \bar{u_{0jt}} = \alpha_s p_{jt} + \xi_{s,1jt} - \mathbb{E}V_{s,jt+1} - \xi_{s,0jt} \tag{21}$$

Rewritting the form of $\mathbb{E}V_{jt+1}$:

$$\mathbb{E}V_{jt+1} = \gamma + \bar{u_{1jt}} - ln(s_{1jt+1}) = \gamma + \alpha_s p_{jt} + \xi_{s,1jt} - ln(s_{1jt+1})$$

Substituting $\mathbb{E}V_{jt+1}$ into equation (22), we have:

$$ln(s_{1jt+1}) - ln(s_{1jt}) + ln(s_{0jt}) = \gamma + \alpha_s(p_{jt+1} - p_{jt}) + (\xi_{s,1jt+1} - \xi_{s,0jt} + \xi_{s,1jt1}) \tag{22}$$

Intuitively, we incorporate the sellers' forward-looking behavior by taking into account the next periods' market share and price in the equation to be estimated.

An identification challenge arises due to the potential correlation between p_j and unobservable characteristics v_j. To address this, I use the aggregate number of link clicks on Lianjia website for type j houses during previous periods as an instrument for price. The number of link clicks serves as a proxy for demand shocks that do not directly impact the current period's supply.

6 Results

6.1 Demand estimation results

The demand estimation results are reported in Table 3. Columns (1) and (2) present the results from the model under the stability assumption, while Columns (3) and (4) show the estimation results from dynamic models where the stability assumption is relaxed. In all of the specifications, I account for a comprehensive set of fixed effects. These include town by house type fixed effects, which absorb differences in location and spatial variations in the representativeness of the existing house data. I also control for quarter fixed effects, which capture the time trend in demand and supply. The outcomes from the model under the stability assumption are similar to those from the more flexible dynamic model.

As expected, the price coefficients are negative and significant in all specifications. The waiting cost coefficient is negative, suggesting the waiting cost's important role in households' utility function. For a $90m^2$ house, the waiting cost is estimated to be around 4% of the total price. Households in wealthier regions are less price sensitive.

Table 3: Demand estimation results

		(1)	(2)	(3)	(4)
		Stability Assumption		Dynamic Model	
price (10K CNY)		-0.946***	-0.801***	-0.855***	-0.696***
		(0.298)	(0.253)	(0.127)	(0.070)
	× rich		0.344**		0.247**
			(0.144)		(0.090)
waiting cost		-0.30***	-0.326***	-0.323***	-0.383***
		(0.113)	(0.108)	(0.058)	(0.017)
	× rich		0.080		0.122
			(0.164)		(0.189)
Subdistrict by house type FE		X	X	X	X
Quarter FE		X	X	X	X
District by year FE		X	X	X	X

Notes: (1) Standard errors are clustered at the product level. *** p<0.01, ** p<0.05, * p<0.1.

6.2 Existing house supply estimation

Table 4 reports the supply estimation results for existing houses. As mentioned in section 4, the supply of the existing houses is modeled as a binary choice problem where the current residents take the price as given and decide whether to sell the house or not. In the same way as in the demand estimation part, I aggregate the existing house at the town/subdistrict by house-type level. The price coefficient is estimated to be 0.543, which is significant at the 1% level. This price coefficient maps to a price elasticity of 2.7, which is comparable to Lee, Ferdowsian, and Yap (2022)'s estimates from Singapore. They adopt a similar approach to estimate the supply.The supply is less elastic than the demand. This is because the supply curve for existing houses is made by house owners, while the demand curve estimated in Table 3 is based on house buyers. Typically, house buyers are younger individuals who do not yet own houses.

Table 4: Supply parameters

price per sq meters	0.543***
	(0.193)
Subdistrict by house type fixed effects	X
Quarter fixed effects	X
District by year fixed effects	X

Notes: Standard errors are clustered at the product level. *** p<0.01, ** p<0.05, * p<0.1.

6.3 Demand model fit

I test demand model's fit by constructing an untargeted moment condition. I utilize the prices of nearby existing houses (after adjusting for differences in transaction taxes and hedonic characteristics such as age) to forecast new house prices without the price ceiling. Then, I compare these forecasts to the predictions from the structural model. I apply the estimated parameters from Equation (20) to adjust the prices of existing houses, ensuring that they are comparable to those of the new houses. To account for factors like location and school district when predicting new house prices, I restrict my analysis to existing houses built after 2005 and located within 1 kilometer of the new houses when predicting new house prices.

More formally, the moment condition can be written as:

$$\frac{\sum_{j,old=1}^{E_{j,new}} p_{j,old} - \beta(X_{j,old} - X_{j,new})}{E_{j,new}} = \widetilde{p}_{jnew,new} \tag{23}$$

Where the left-hand side denotes the predicted new house price based on nearby existing houses. $E_{j,new}$ is the number of existing houses built after 2005 and within 1 kilometer of new house j, new. The vector X contains age, and the number of bedrooms, bathrooms, living rooms, and kitchens. $\widetilde{p_{jnew,new}}$ denotes the predicted new house price from the structural model.

I plot the predicted prices for new houses without a price ceiling (derived from nearby existing houses) given by Equation (23) against the counterfactual price for new houses without a price ceiling (as per the structural model), denoted by $\widetilde{p_{jnew,new}}$ in Figure 5. If the model were a perfect fit, the fitted line would coincide with the 45-degree line. When applying the current model which incorporates waiting and queuing, the fitted line is not statistically distinguishable from the 45-degree line, suggesting model's good fit.

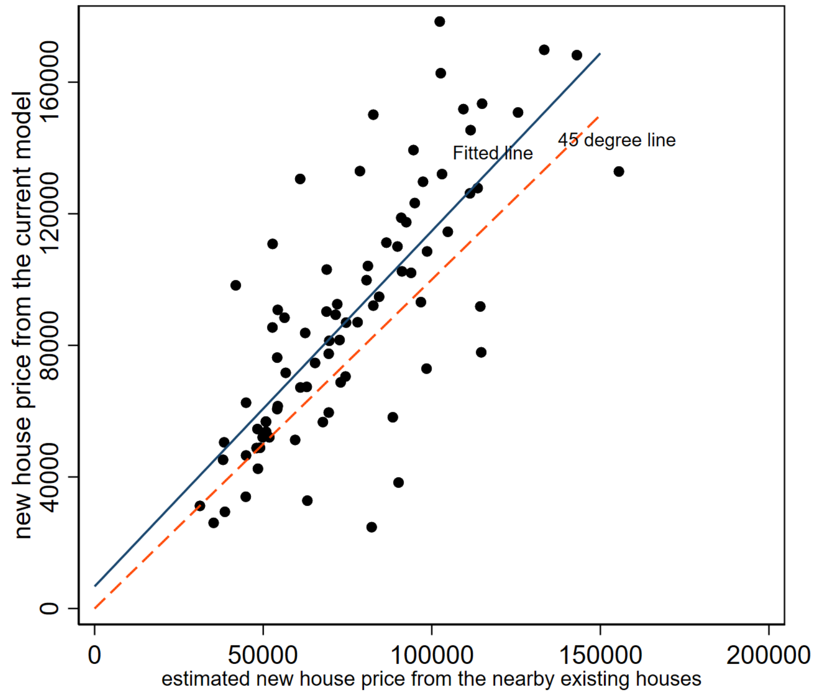
7 Counterfactual Analyses

In this section, I use the model parameters estimated from Table 3 and 4 to evaluate the overall welfare impact of the price ceiling in Shanghai. Then, I explore the welfare and distributional impact of alternative policies, such as distributing a housing purchase voucher and increasing the supply.

7.1 Without the price ceiling

The first step in this counterfactual analysis involves searching for a set of prices for both new and existing houses that equates the demand with the supply under the scenario without the price ceiling. Once the equilibrium is determined, I calculate the corresponding demand, supply, and the resulting consumer, existing house

Figure 5: Model fit



Notes: (1) The y-axis represents the new house price *without price ceiling* based on the current model parameters. The x-axis represents the estimated new house price without price ceiling using the nearby existing house information. (2) Each dot represents a new apartment complex. In this figure, I exclude new apartment complexes with fewer than three nearby transacted existing houses.

seller, and producer surplus.

The welfare comparison between the current scenario with a price ceiling and the counterfactual scenario without a price ceiling is reported in the first two rows in Table 5. The analysis reveals that the total welfare losses attributed to the price ceiling in Shanghai from 2018 to 2020 amounts to 13.1 billion USD, with the reduction in producer surplus being the primary contributing factor. Consumer surplus only increases by 1.3 billion USD. A substantial portion of the consumer surplus gain from lower prices is offset by the waiting costs and misallocation (i.e., house buyers with a high willingness to pay cannot purchase a house due to the lottery). The estimated waiting costs stand at 5.1 billion USD, and the misallocation in the new house market amounts to 6.8 billion USD. The Price ceiling also has a minor negative impact on the existing house seller surplus (SS) due to the slight reduction in the existing house prices. The slight negative impact on the existing house seller surplus is a consequence of some households, who initially had considered buying existing houses without a price ceiling, now opting to join the queue for new houses due to the lower price's attractiveness when a price ceiling is imposed in the new house market.

In the rightmost column, I report the impact of the price ceiling on the *overall* housing price *faced by the consumer* based on the following formula: Price impact $= \Delta p_{it} \cdot \frac{D_{wopc,it}}{\sum D_{wopc,it}}$.[7] Where $D_{wopc,it}$ denotes the demand of house product i in time t when there is no price ceiling, and Δp_{it} denotes the percent change in price faced by the consumers.[8] The results suggest that the price ceiling policy leads to a 1.6 percentage point reductions in the overall housing price in Shanghai from 2018 to 2020.

Table 5: Welfare and price impact of the without price ceiling

in billion USD	CS	PS	SS	total surplus	Δ welfare	Δp
w/o price ceiling (benchmark)	100.94	109.69-C	115.77	326.40-C		
with price ceiling (current)	102.25	96.17-C	114.87	313.29-C	-13.11	-0.016

Note: (1) CS, PS, SS denote the consumer surplus, new house developer (producer) surplus, and existing house seller surplus, respectively; (2) The exchange rate between the US dollar and the Chinese yuan is 7. (3) Δp denotes the change of the price due to the price ceiling (compared with the counterfactual scenario without price ceiling). (4) All numbers are in billion USD, except for the numbers in the rightmost column.

7.2 Housing vouchers to all houses

One alternative policy to the price ceiling is housing purchase vouchers. In theory, distributing vouchers has several advantages over a price ceiling. First, consumers no longer need to wait to purchase houses. Second, price is still an effective tool

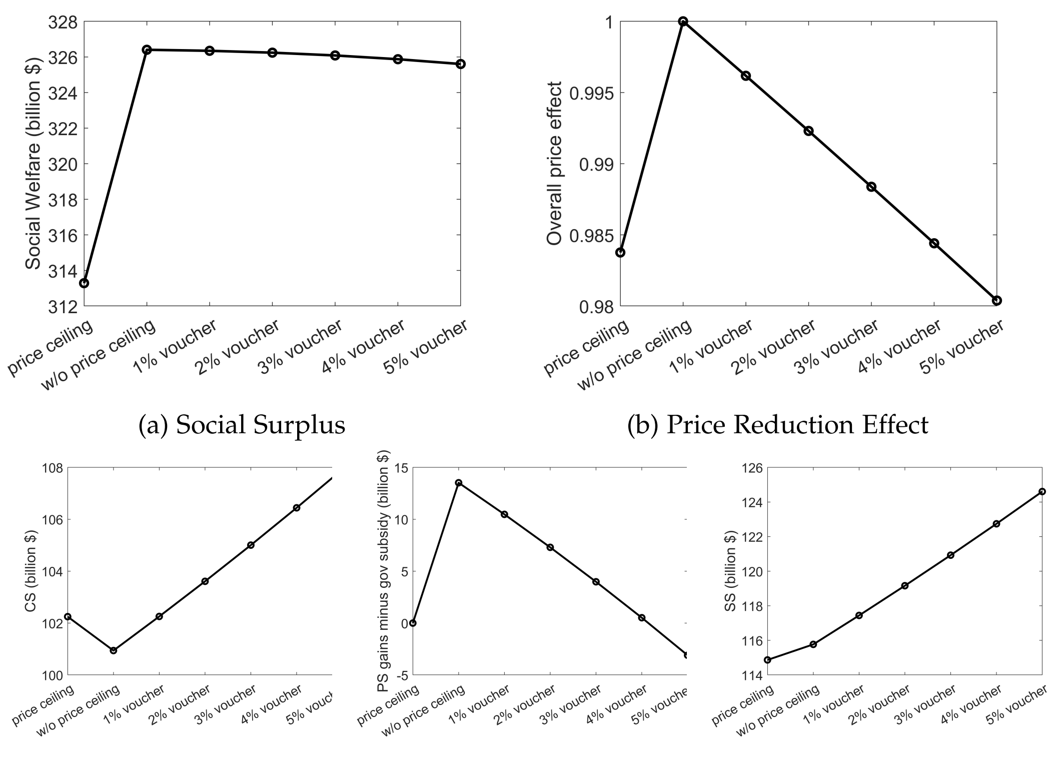
[7] I account for the impact of price ceiling on both new and existing house price.

[8] More formally, $\Delta p_{it} = \frac{p_{it,n} \cdot (1-\text{voucher}) - p_{it,wopc}}{p_{it,wopc}}$, where $p_{it,n}$ is the searched equilibrium price under different counterfactual scenarios,

for sorting consumers based on their willingness to pay. Thus, misallocation is reduced. This approach could potentially improve social welfare compared to price ceilings, provided that the deadweight loss linked to vouchers is less than the combined waiting costs and misallocation engendered by price ceilings. Additionally, the distribution of vouchers can also achieve the price reduction effects as the price ceilings.

The expense associated with the vouchers could be financed by imposing a lump-sum tax on the developers. Developers would be inclined to bear this tax as long as it is less than the losses they would incur due to the price ceiling. For this analysis, we contemplate a range of voucher percentages from 1% to 5%, applicable to *all houses*.

Figure 6: Housing vouchers to all houses



(a) Social Surplus (b) Price Reduction Effect

(c) Consumer Surplus (d) Net Producer Surplus (e) Seller surplus

Notes: (1) CS, PS, SS denote the consumer surplus, new house developer (producer) surplus, and existing house seller surplus, respectively; (2) Panel (b) represents the reduction in housing price faced by *the consumers*; (3) The outcome variable in Panel (d) is calculated as follows: Net PS gains = $PS_{voucher} - PS_{ceiling} -$ gov subsidy. This is based on the assumption that the government subsidies for vouchers are covered by a lump-sum tax levied on new house developers.

The results are presented in Figure 6. Panel (a) indicates that offering a housing voucher increases the social surplus. In all five purchase voucher scenarios, the social surplus nearly matches levels seen without a price ceiling. This suggests that the deadweight loss from the voucher is significantly less than the welfare losses due to a price ceiling.

Panel (b) reports the vouchers' price reduction effect faced by the consumers. Predictably, the larger the voucher, the more pronounced the price reduction. A 4% housing voucher offers a price reduction comparable to that of the price ceiling.

Panels (c), (d), and (e) break down changes in the social surplus among consumers, producers, and existing home sellers. Note that the variable in y-axis is the net producer surplus. The calculation of the net producer surplus is based on the assumption that government subsidies for vouchers are covered by a lump-sum tax levied on producers. Specifically, the y-axis in Panel (d) is: $PS_{voucher} - PS_{ceiling} -$ gov subsidy. The results suggest that for housing vouchers of 4% or less, the increase in producer surplus is sufficient to offset government subsidies. This means new house developers can still benefit more than in the price ceiling scenario, even if they shoulder all of the costs for distributing vouchers up to 4%.

In sum, Figure 6 indicates that replacing the price ceiling with a 4% purchase voucher policy can achieve a quasi-Pareto improvement. Such a policy would be to benefit house buyers, existing house sellers, and new house developers, while also achieving a comparable decrease in the housing prices faced by the consumers.

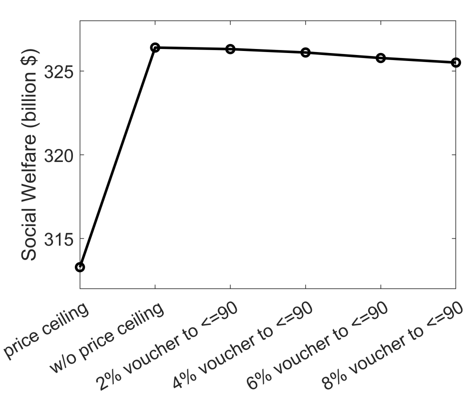
7.3 Housing vouchers for small houses

A primary challenge in Shanghai's housing market is the unaffordability of homes for the middle class. One potential solution is a targeted housing voucher system focused on smaller houses, with the aim of more accessible housing for the middle class. For the purposes of this study, we set a threshold of 90 m^2 to delineate "small" houses and explore the outcomes of different voucher types. The findings are illustrated in Figure 7.

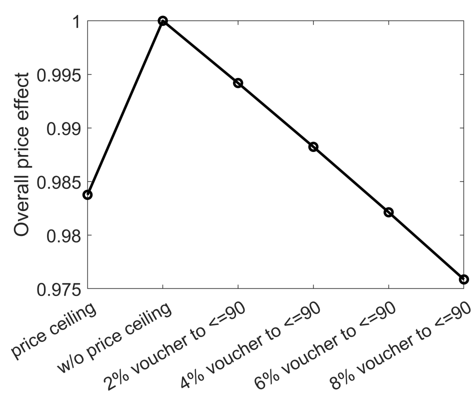
The outcomes are similar to those presented in Figure 6. Offering vouchers for homes smaller than $90m^2$ can markedly increase social welfare. Distributing a 6% voucher for homes below $90m^2$ could achieve a price reduction comparable to that of a price ceiling. Moreover, the rise in producer surplus, when compared to the price ceiling scenario, suffices to offset the subsidies required for voucher distribution, implying that the developers can still be better off even if the government subsidies for vouchers are fully paid by them. Therefore, we can also achieve a Pareto Improvement in this scenario, with the new house developers, house buyers, existing house sellers all better off.

I discuss the distributional effects of varying policies in Section 7.5.

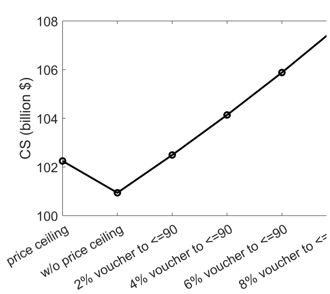
Figure 7: Housing vouchers to houses $\leq 90m^2$



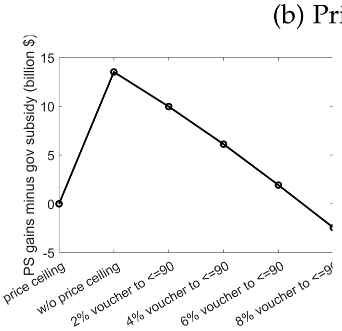
(a) Social Surplus



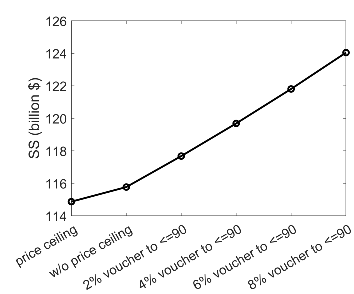
(b) Price Reduction Effect



(c) Consumer Surplus



(d) Net Producer Surplus



(e) Seller surplus

Notes: (1) CS, PS, SS denote the consumer surplus, new house developer (producer) surplus, and existing house seller surplus, respectively; (2) Panel (b) represents the reduction in housing price faced by *the consumers*; (3) The outcome variable in Panel (d) is calculated as follows: Net PS gains = $PS_{voucher} - PS_{ceiling} -$ gov subsidy. This is based on the assumption that the government subsidies for vouchers are covered by a lump-sum tax levied on new house developers.

7.4 Increase the new house supply

Another common method for improving housing affordability is to augment the supply. In this analysis, we investigate a hypothetical scenario in which the government implements measures to enhance the new house supply by 50%. One strategy reaching this growth could be relaxing existing regulations concerning the floor-area ratio (FAR). Generally, the upper bound for FAR in new residential buildings in Shanghai ranges from 2 to 2.5. This figure stands in contrast to higher ratios found in other major cities; for example, the average FAR in Manhattan, New York City, is 5.84 (Barr and Cohen, 2014). These comparisons suggest that there is considerable room for the government to ease regulations on floor area, creating the potential for an increase in housing supply.

The results are reported in Table 6. One difficulty in the counterfactual welfare calculation is that we do not know the construction cost of extra units. I consider a conservative scenario and a realistic scenario of the size of the construction costs. In the conservative scenario, I assume that the construction cost of the additional units equals the sales revenue of these units (the third row). In the more realistic scenario (the last row), the construction cost of the additional units is assumed to be 40% of the sales revenue. The results reveal that relaxing the floor area regulation to increase the new housing supply by 50% can lead to a 1.6% reduction in the *overall* housing price in Shanghai, slightly larger than the effect of the price ceiling policy. Even under the most conservative scenario, relaxing the FAR upper bound by 50% can increase the social welfare. The increase in social welfare under the more realistic scenario can be as high as 22.2 billion USD. Notably, consumer surplus also increases significantly.

7.5 The distributional impact of different policies

In this section, I explore the distributional impacts of various housing policies, namely: the current price ceiling, a 4% housing voucher applied to all houses, a 6% housing voucher specific to houses under 90 m^2, and an increase in the Floor-Area

Table 6: Welfare and price impact of relaxing the FAR regulation

in billion USD	CS	PS	SS	total surplus	Δ welfare	Δp
w/o price ceiling (benchmark)	100.94	109.69-C	115.77	326.40-C		
with price ceiling (current)	102.25	96.17-C	114.87	313.29-C	-13.11	-0.016
⇈ new house supply (conservative)	112.00	100.96-C	114.37	327.33-C	0.93	-0.021
⇈ new house supply (realistic)	112.00	122.20-C	114.37	348.57-C	22.17	-0.021

Note: (1) CS, PS, SS denote the consumer surplus, new house developer (producer) surplus, and existing house seller surplus, respectively. (2) The exchange rate between the US dollar and the Chinese yuan is 7. (3) Δp denotes the change of the price due to the price ceiling (compared with the counterfactual scenario without price ceiling). (4) All numbers are in billion USD, except for the numbers in the rightmost column.

Ratio (FAR) upper limit by 50%[9]. Since I cannot directly observe household incomes, I report the effect of various policies on the housing prices faced by households across different percentiles. Households who purchase more expensive houses are more likely to be wealthier. The results are depicted in Figure 8. The total housing prices are segmented into ten intervals along the x-axis, with the y-axis representing the reduction in housing prices faced by consumers.

The blue line represents the status quo, the current price ceiling, which predominantly benefits buyers of top 20% of the houses. This is because, new houses are usually larger and more expensive than the existing ones.

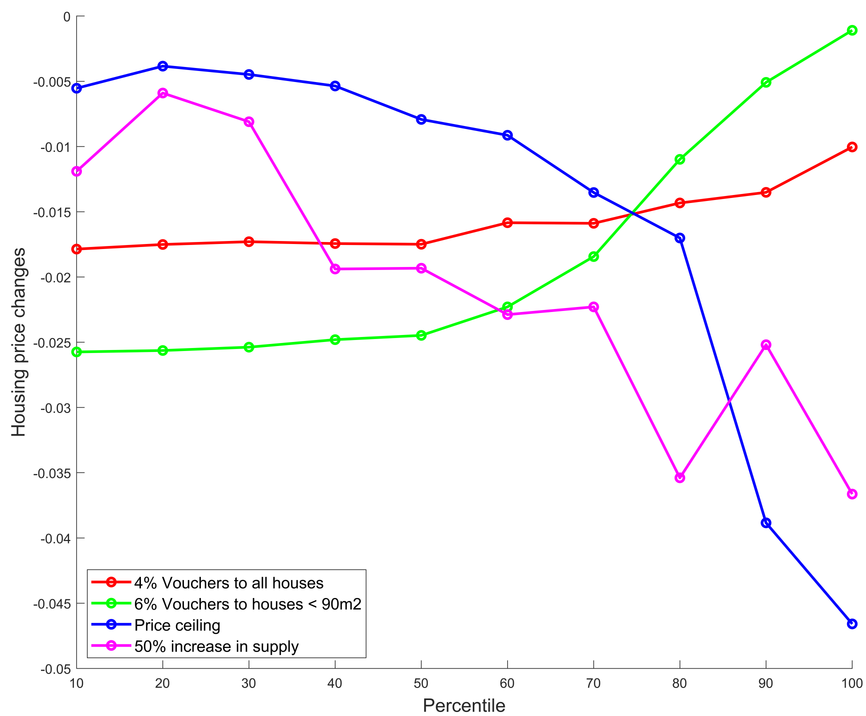
The purple line suggests that the distributional impact of relaxing the FAR by 50% is similar to the price ceiling policy. This similarity arises because both policies primarily affect the pricing of new houses, which are generally more expensive.

The red line indicates that offering a 4% housing voucher to all houses would benefit all house buyers roughly equally. In contrast, the green line presents a scenario where a 6% housing voucher is provided for houses up to 90m^2. This strategy mainly benefits house buyers in the bottom 50 percentiles, with small impact on the top 20 percentiles. Therefore, offering housing purchase vouchers to smaller houses

[9]The choice of a 4% universal housing voucher and a 6% voucher for smaller homes (<90 m^2) stems from their ability to effectuate a housing price reduction similar to the price ceiling. Moreover, the required government subsidies can be funded by the gains in producer surplus.

($90m^2$ or below) could enhance affordability for less affluent buyers in Shanghai, who are often younger and may encompass many new migrants.

Figure 8: Distributional impact of different policies



Notes: In x-axis, I divide the houses into ten groups based on their current total transaction price. the y-axis portrays the reduction in housing price faced by *the consumers*.

7.6 Unpacking the effect of waiting cost: waiting to sorting

In this section, I explore a counterfactual scenario by setting the waiting cost parameter (β_c) to zero, while keeping the other parameters and the price ceiling extent unchanged. As demonstrated by the illustrative model in Section 2, an increase in the waiting cost can lead to a shorter waiting line, effectively sorting out consumers with a lower willingness to pay. On one hand, the waiting cost itself generates welfare losses. On the other hand, the inclusion of the waiting costs reduces misallocation due to the sorting effect of waiting. The primary objective of this section is to test the implications of the waiting to sorting channel.

The results are presented in Table 7. The welfare losses are decomposed into three components: waiting costs, misallocation in the new housing market, and spillover effects from the existing housing market (not reported here). When the waiting cost parameter β_c is decreased to zero, the welfare losses due to misallocation in the new house market increase from 8 billion USD to 9.8 billion USD. This increase occurs because a low waiting cost attracts consumers with a low willingness to pay to join the new house waiting line. However, the lottery used to allocate the houses cannot differentiate between consumers with low or high willingness to pay, thereby exacerbating the misallocation. Despite the increase in the welfare losses from misallocation, the total welfare loss is still higher when the waiting cost is positive, as the waiting cost itself accounts for welfare losses of 5.1 billion USD.

Table 7: Waiting costs decrease to zero: waiting to sorting

in billion USD	CS		SS	PS	total surplus	welfare decomposition	
	new	existing				waiting cost	misallocation
$\beta_c = 0$	23.25	86.02	111.19	96.17-C	316.62-C	0	9.78
with price ceiling	21.09	81.16	114.87	96.17-C	313.29-C	5.1	8.0

Note: (1) CS, PS, SS denote the consumer surplus, new house developer (producer) surplus, and existing house seller surplus, respectively. (2) The exchange rate between the US dollar and the Chinese yuan is 7. (3) All numbers are in billion USD.

8 Conclusion

This paper proposes a novel framework for studying the equilibrium effect of price control policies. In this framework, I consider the option for consumers to wait and re-enter the market if items are not immediately allocated due to the excess demand. I show that this waiting aspect, often overlooked in prior research on price ceilings, is pivotal in welfare calculations, and counterfactual policy design.

I have applied this model to study the price ceiling in Shanghai. The government imposes the price ceiling on new houses to improve housing ability. It requires the price capped new houses must be sold by lottery, while allowing the market to determine the prices of existing houses. I assembled a new dataset that contains information regarding the sales of new and existing houses, the price ceiling set by the government, and household lottery participation records. Through structural modeling, I estimate household demand, housing supply, and the associated waiting costs. I find that the price ceiling on new houses reduces the housing price by 1.6%, while it causes a total welfare losses of 13.1 billion US dollars. Despite a modest increase in consumer surplus, the majority of the gains from lower prices were offset by waiting costs and misallocation. Further analyses suggest that the price ceiling primarily benefits the buyers of more expensive houses.

Counterfactual analyses offer alternative solutions to housing affordability. I find that distributing a housing voucher instead of a price ceiling can achieve similar price reduction outcomes, while significantly reducing welfare losses and achieving more equitable outcomes. For instance, distributing a 6% housing voucher for houses up to $90m^2$ can primarily benefit house buyers in the bottom 50 percentiles, while the welfare losses can be reduced to 0.6 billion USD. The cost of distributing the housing voucher could be financed by levying a lump-sum tax on new house developer. The developers would be willing to pay this tax as long as it is smaller than their losses from the price ceiling. Relaxing the regulations on floor area ratio (FAR) by 50% can similarly reduce housing prices while also significantly enhancing social welfare.

The framework developed in this paper could also be applied to study price ceilings in other sectors, such as the healthcare industry, and the U.S. work visa and green card lottery, where waiting costs and misallocation are also severe.

A Appendix

A.1 The impact of new house price ceiling on nearby existing house price

The objective of this section is to present reduced-form evidence on the impact of the new house price ceiling on nearby existing house prices. The primary independent variable used in the analysis is the intensity of the price ceiling (PCI_1) for new apartments, calculated as the proportion of units subject to a binding price ceiling at the subdistrict level, following the method prposed by Autor, Palmer, and Pathak (2014). To ensure the robustness of the results, an additional index, PCI_2, is constructed. PCI_2 represents the average probability of winning a new house lottery in a subdistrict or town. Both PCI_1 and PCI_2 are standardized to a normal distribution with a mean of 0 and a standard deviation of 1. The difference-in-differences equation can be written as:

$$log(p_{i,s}) = \gamma_z + \gamma_t + \beta' \cdot X_{i,s,t} + \lambda \cdot PCI_{i,s} * Post_t + \epsilon_{i,s,t} \tag{A1}$$

Where γ_s and γ_t denote the subdistrict and year-quarter fixed effect, respectively. $X_{i,z,t}$ is a set of controls, including the number of bedrooms, livingrooms, bathrooms, kitchens, area, and whether the houses have an elevator. The results are reported in Table A1.

The results presented in Table A1 indicate that the new house price ceiling has a small and imprecise negative impact on the prices of existing houses in nearby areas. These results are further illustrated through the visual representation of the difference-in-differences regression in Figure A1. The parallel trend assumption is met, and the figure corroborates with the findings in difference-in-differences analysis that the effect of the new house price ceiling on the prices of existing houses is limited.

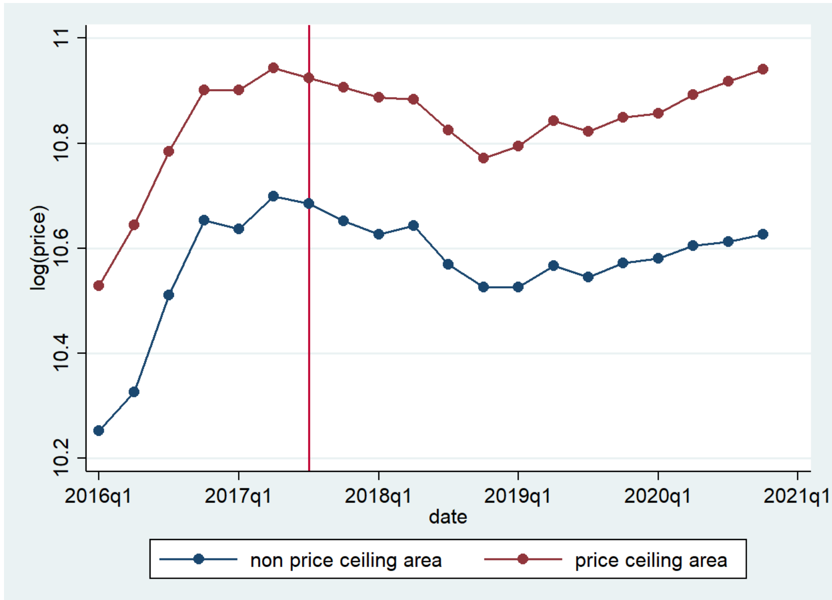
The findings presented in Table A1 and Figure A1 contradict the predictions of the static model, as discussed in McDonald and McMillen (2010) and Mense,

Table A1: The impact of the new house price ceiling on the existing house price

	ln(existing house price)			
	(1)	(2)	(3)	(4)
PCI1*post	-0.00581	-0.00388		
	(0.00658)	(0.00615)		
PCI2*post			-0.0123*	-0.00939
			(0.00637)	(0.00613)
year-quarter FE	X	X	X	X
subdistrict FE	X	X	X	X
controls		X		X
Observations	136576	129719	136576	129719
R-squared	0.689	0.707	0.689	0.708

Michelsen, and Kholodilin (2019). According to the static analysis, the implementation of a price ceiling on new houses should lead to an increase in the price of existing houses since buyers who are willing to pay a high price for new houses but cannot obtain them would switch to the existing house market. This is driven by an implicitly imposed assumption: buyers can not re-enter the market again in the future. However, the dynamic framework in this paper does not impose such an assumption. In the dynamic price ceiling model, households who are unsuccessful in the current new house lottery can still purchase either new or existing houses in the next period. They can continue to participate until they win the new house lottery or choose to purchase an existing house. Despite households having to queue and wait for new houses, the lower price due to the price ceiling makes the new houses more appealing. Consequently, some households who initially opted to buy existing houses when there was no price ceiling will switch to the queuing line for new houses, which drives down the price of existing houses. Given the heterogeneity in prices and waiting costs, the direction of change in existing house prices becomes ambiguous. The counterfactual analysis presented in Section 8 of the paper provides additional results on how existing house prices respond to the price ceiling on new houses.

Figure A1: Existing house price in the price ceiling area versus non-price ceiling area



Notes: the non-price ceiling area is defined as the subdistrict/towns without a price ceiling or its PCI1 lies in the 25th percentile. The price ceiling area is its complement.

A.2 Instruments

Table A2 presents the first stage regression results for the demand estimation. The dependent variables in column (1), (2), (3) are price ceiling for the new houses, price for the existing houses, and the expected number of entries to win the new house lottery, respectively. As mentioned in section 5, I use the cost of the land as the instrument for the price ceiling for the new houses, the number of nearby house listings as the instrument for the price for the existing houses, and the supply of the new houses as the instrument for the number of expected entries to win the lottery. Product fixed effects are controlled in column (1) and (3). Product fixed effects, quarter fixed effects, and district by year fixed effects are controlled in all specifications.

The results in Table A2 suggest a strong relationship between the instruments and the endogenous variables in the demand estimation.

Table A2: Demand instruments: first stage

	(1) p_{new}	(2) p_{old}	(3) $\frac{1-Pr_j}{Pr_j}$
land cost	0.228***		-0.136
	(0.059)		(0.139)
number of nearby houses' listings		-1.09***	
		(0.249)	
supply of the new houses	0.146**		-0.0039***
	(0.063)		(0.0011)
Product F.E.	Y	Y	Y
Quarter F.E.	Y	Y	Y
district by year F.E.	Y	Y	Y

Notes: Standard errors are clustered at the product level. *** p<0.01, ** p<0.05, * p<0.1.

References

Agarwal, Nikhil, Itai Ashlagi, Michael A Rees, Paulo Somaini, and Daniel Waldinger. 2021. "Equilibrium allocations under alternative waitlist designs: Evidence from deceased donor kidneys." *Econometrica* 89 (1):37–76.

Agarwal, Sumit, Keyang Li, Yu Qin, Jing Wu, and Jubo Yan. 2020. "Tax evasion, capital gains taxes, and the housing market." *Journal of Public Economics* 188:104222.

Arcidiacono, Peter and Robert A Miller. 2011. "Conditional choice probability estimation of dynamic discrete choice models with unobserved heterogeneity." *Econometrica* 79 (6):1823–1867.

Autor, David H, Christopher J Palmer, and Parag A Pathak. 2014. "Housing market spillovers: Evidence from the end of rent control in Cambridge, Massachusetts." *Journal of Political Economy* 122 (3):661–717.

Bai, ChongEn, Qi Li, and Min Ouyang. 2014. "Property taxes and home prices: A tale of two cities." *Journal of Econometrics* 180 (1):1–15.

Barr, Jason and Jeffrey P Cohen. 2014. "The floor area ratio gradient: New York City, 1890–2009." *Regional Science and Urban Economics* 48:110–119.

Bayer, Patrick, Fernando Ferreira, and Robert McMillan. 2007. "A unified framework for measuring preferences for schools and neighborhoods." *Journal of political economy* 115 (4):588–638.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile prices in market equilibrium." *Econometrica: Journal of the Econometric Society* :841–890.

———. 2004. "Differentiated products demand systems from a combination of micro and macro data: The new car market." *Journal of political Economy* 112 (1):68–105.

Caetano, Gregorio. 2019. "Neighborhood sorting and the value of public school quality." *Journal of Urban Economics* 114:103193.

Calder-Wang, Sophie. 2021. "The distributional impact of the sharing economy on the housing market." *Available at SSRN 3908062* .

Chen, Ting and James Kai-sing Kung. 2019. "Busting the "Princelings": The campaign against corruption in China's primary land market." *The Quarterly Jour-*

nal of Economics 134 (1):185–226.

Deacon, Robert T and Jon Sonstelie. 1985. "Rationing by waiting and the value of time: Results from a natural experiment." *Journal of Political Economy* 93 (4):627–647.

Diamond, Rebecca, Tim McQuade, and Franklin Qian. 2019. "The effects of rent control expansion on tenants, landlords, and inequality: Evidence from San Francisco." *American Economic Review* 109 (9):3365–94.

Eriksen, Michael D and Amanda Ross. 2015. "Housing vouchers and the price of rental housing." *American Economic Journal: Economic Policy* 7 (3):154–176.

Galiani, Sebastian, Alvin Murphy, and Juan Pantano. 2015. "Estimating neighborhood choice models: Lessons from a housing assistance experiment." *American Economic Review* 105 (11):3385–3415.

Glaeser, Edward, Wei Huang, Yueran Ma, and Andrei Shleifer. 2017. "A real estate boom with Chinese characteristics." *Journal of Economic Perspectives* 31 (1):93–116.

Glaeser, Edward L. 1996. "The social costs of rent control revisited." *NBER Working Paper* (w5441).

Glaeser, Edward L and Erzo FP Luttmer. 2003. "The misallocation of housing under rent control." *American Economic Review* 93 (4):1027–1046.

Gowrisankaran, Gautam and Marc Rysman. 2012. "Dynamics of consumer demand for new durable goods." *Journal of political Economy* 120 (6):1173–1219.

Lee, Kwok Hao, Andrew Ferdowsian, and Luther Yap. 2022. "The Dynamic Allocation of Public Housing: Policy and Spillovers." .

Li, Shanjun. 2018. "Better lucky than rich? Welfare analysis of automobile licence allocations in Beijing and Shanghai." *The Review of Economic Studies* 85 (4):2389–2428.

McDonald, John F and Daniel P McMillen. 2010. *Urban economics and real estate: theory and policy*. John Wiley & Sons.

Mense, Andreas, Claus Michelsen, and Konstantin A Kholodilin. 2019. "The effects of second-generation rent control on land values." In *AEA Papers and Proceedings*, vol. 109. 385–88.

Platt, Brennan C. 2009. "Queue-rationed equilibria with fixed costs of waiting." *Economic Theory* 40:247–274.

Sims, David P. 2007. "Out of control: What can we learn from the end of Massachusetts rent control?" *Journal of Urban Economics* 61 (1):129–151.

Susin, Scott. 2002. "Rent vouchers and the price of low-income housing." *Journal of Public Economics* 83 (1):109–152.

Waldinger, Daniel. 2021. "Targeting in-kind transfers through market design: A revealed preference analysis of public housing allocation." *American Economic Review* 111 (8):2660–2696.

Wetzstein, Steffen. 2017. "The global urban housing affordability crisis." *Urban studies* 54 (14):3159–3177.