

Public Housing at Scale: Dynamics, Policies, and Spillovers

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Abstract

We consider the design of a large-scale public housing program where consumers face dynamic tradeoffs over apartments rationed via lotteries and prices. We show, theoretically and empirically, that changing rules complements increasing supply. First, we present a motivating example in which supplying more housing leads households to strategically delay their applications. By waiting for “better” developments arriving tomorrow, households forgo mediocre developments available today, resulting in more vacancies. Turning to the data from the mechanism, we formulate a dynamic choice model over housing lotteries and estimate it. Under the existing mechanism, we find that increasing supply fails to lower wait times. However, when a strategyproof mechanism is implemented, vacancies and wait times fall, but prices on the secondary market rise. Under this new mechanism, building more apartments lowers wait times and reduces the upward pricing pressure on the secondary market.

Keywords: Public housing, Market design, Inequality, Dynamic discrete choice

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1 Introduction

This paper considers the design of public housing policy. Governments build public housing, then rent or sell these apartments below market prices.² In these programs, governments seek to minimize apartment vacancies, lower wait times for needy households, ensure price stability in related housing markets, among other objectives. Insights from market design suggest that tweaking allocation rules may help achieve these outcomes.³ Meanwhile, popular discourse emphasizes building more housing. How do these two policies impact our desiderata, and how does adding supply interact with changing the rules?

To answer these questions, we form a dynamic choice model and estimate it on novel data from Singapore. In counterfactual simulations, we find that better rules and adding supply complement each other. Our proposed mechanism reduces vacancies and wait times, but raises prices on the aftermarket for apartments. To relieve this upward pricing pressure, building more apartments can help, while also keeping wait times low. However, in the existing mechanism, at the margin, adding supply is ineffective at reducing wait times.

We study a large-scale public housing program, the Singapore Build-to-Order mechanism (BTO), described in Section 3. In Singapore, the government supplies 80% of the housing stock, seeking to boost fertility, ensure racial and socioeconomic mixing, and, most importantly, to encourage homeownership. In each quarter, different developments are offered within a period and across time; households may express a preference for at most one such development. These apartments are rationed by lottery and can be resold by their occupants on an aftermarket. The government subsidizes matched applicants in two ways: implicitly, by pricing apartments below their counterparts on the secondary market; and explicitly, by giving the poor a further discount. Ultimately, BTO is a clean setting for us to capture how young households behave when they apply for public housing.

In Section 6, we provide a theoretical example showing that injecting supply may exacerbate the problem of *rational delay*, harming applicants in equilibrium. In the current mechanism, young households are incentivized to wait for better apartments arriving next period, leaving today's apartments empty.⁴ This example suggests the following questions: We can precisely target rational delay using a mechanism that eliminates intertemporal risk. How does our proposed mechanism impact vacancies, wait times, and prices on the secondary market? Moreover, what

²Public housing is a common form of housing assistance worldwide. For instance, 45% of residents in Hong Kong live in public housing ([Hong Kong Housing Authority 2017](#)), as do 80% in Singapore ([Yuen 2021](#)). Public housing allocation has been studied carefully in the contexts of Cambridge, MA ([Waldfinger 2021](#)) and in Amsterdam ([Van Dijk 2019](#)). Unlike in the latter paper, we do not speak to the effect of selection into/out of public housing on life outcomes, like labor market participation, educational attainment, and criminal behavior (see, e.g., [Chyn 2018](#)).

³For instance, better rules to allocate kidneys can improve patient welfare by an amount “equivalent to an 18.2% increase in donor supply” ([Agarwal et al. 2021a](#)). For a review of why governments disburse transfers in kind, see [Currie and Gahvari \(2008\)](#). For a theoretical analysis of rationing housing assistance via lotteries and waitlists, see [Arnotti and Shi \(2020\)](#). For why the Singapore government provides public housing, see Subsection 3.2.

⁴In the February 2023 BTO exercise, a 23-year-old university student stated that she “chose to sit out the February exercise because they preferred to save their application for May to try for a unit in Serangoon,” a popular neighborhood ([Ong 2023](#)).

are the effects of a small supply increase on these outcomes, both in the actual mechanism and our proposed one?

To answer these questions, we consider two policy interventions. To shut down intertemporal risk, we simulate a dynamic version of Random Serial Dictatorship, in which households express preferences over housing units that may be available in the future. Meanwhile, to implement a small supply increase, we build 10% more apartments in oversubscribed developments.

To evaluate the effects of these interventions, in Section 7, we set up a dynamic choice model over housing lotteries, which we take to the data. In this model, new housing developments arrive exogenously. Young households are born rich or poor. In each BTO cycle, given the developments on offer, as well as the prices of apartments on the secondary market, these households can select one development, take an apartment on the secondary market, or wait till the next period. Waiting can be rational because, in the mechanism, reneging on an offered apartment is costly. These potential applicants trade off applying to a safe development today, trying for a risky but attractive development, and waiting for “better” developments in the next cycle. Finally, to close the model, on the secondary market, existing owner-occupiers observe the price of their apartment and decide whether to continue living in it or to sell it off and exit the market. These owner-occupiers trade off selling their apartment today against selling for a higher price tomorrow. In equilibrium, the BTO mechanism clears by lottery odds, while the secondary market clears by price.

We take this model to the rich data described in Section 4. In the primary market, we see every offered development, as well as its characteristics and the number of young households who applied to it. Moreover, on the secondary market, we see all transactions that have transpired.

With these data, we undertake descriptive analysis in Section 5, exhibiting development characteristics and dynamics that influence BTO demand. More young households apply to developments that are closer downtown and to the nearest metro stop, among other amenities. Moreover, dynamics matter. In any given BTO cycle, average distances to nearby amenities do not predict total applications. Yet, when comparing pairs of cycles adjacent in time, more attractive choice sets do predict more applications. These observations bridge a gap between the data and our analysis of new rules and larger supply, but do not close it: Equilibria in our counterfactuals not only feature dynamics, but also endogenous lottery odds and aftermarket prices.

Cognizant of the limitations of descriptive analysis, we estimate our proposed model for the 2012-2015 BTO cycles in Section 8. On the supply side, we exploit the fact that selling off one’s apartment is a terminal action (Arcidiacono and Miller 2011), so the price elasticity of supply can be recovered using a static instrumental variables (IV) regression. This elasticity is identified by variation across mover shares and prices by apartment size by neighborhood. To deal with unobserved supply shifters, we instrument for price using demand shocks, including the timing of changes in the government’s subsidy scheme and eligibility for the BTO mechanism.

We also estimate a dynamic random coefficients demand model over new developments and apartments currently in circulation (see, e.g., Gowrisankaran and Rysman 2012). Variation in

development characteristics within a period, as well as choice sets across periods, identifies each applicant’s preference parameters. Additionally, variation in subsidies disbursed by income type allows us to disentangle how sensitive the poor and rich are to prices. To deal with unobserved development quality, we instrument for price using cost shifters and the timing of a policy change affecting households buying multiple properties. We combine these instruments in a Differentiation IV framework ([Gandhi and Houde 2021](#)).

We show, in Section 9, that our parameter estimates are plausible and our model fits the data well. Our demand model successfully recovers that unobserved development amenities are orthogonal to various observed amenities. The demand model also does well on untargeted moments: the recovered residuals do not capture a time trend or amenity from having a (non-prestigious) school nearby. Moreover, in our simulations, we find that most applicants do make less than four applications, corroborating a ministerial response to a question posed in the Singapore parliament.

In our counterfactuals, described in Section 10, we find that better rules complement higher supply. Suppose the Singapore government (1) eliminated intertemporal risk; and (2) built 10% more apartments in oversubscribed developments. Then, vacancies fall from 12% to 10%; meanwhile, wait times fall by 8% for the poor and 23% for the rich. Young households gain from being allowed to list two developments in the same period and possibly exiting early. Exiting early pushes up prices on the secondary market by 9%, or 12% in the case without additional supply. As in our theoretical example, it is ineffective to add supply without changing the rules. Under the current mechanism, the demand response eclipses the supply increase, raising vacancies from 12% to 16% while leaving wait times unchanged. This behavior arises because marginal agents switch from less desirable developments today and apply to better developments next period, leaving today’s developments empty. Thus, in a congested market, when dynamic incentives are influenced by supply, increasing it is not a panacea. Policymakers should also pay attention to the rules under which goods are allocated, so that their constituents can best utilize the additional supply.

2 Recent Literature

This paper speaks to four strands of literature in Economics. Our core contribution speaks to the literature on centralized assignment mechanisms ([Abdulkadiroğlu, Agarwal, and Pathak 2017](#); [Agarwal and Somaini 2018](#); [Fack, Grenet, and He 2019](#); [Hastings, Kane, and Staiger 2009](#); [Narita 2018](#)). Our paper is most closely related to four papers. The first, [Verdier and Reeling \(2021\)](#), focuses on the dynamic assignment of bear hunting licenses with accumulated “preference points” in Michigan.⁵ The second, [Agarwal et al. \(2021a\)](#), focuses on the allocation of deceased donor kidneys as an optimal stopping problem. The third and fourth, [Waldinger \(2021\)](#) and [Naik](#)

⁵In follow-up work, [Reeling, Verdier, and Lupi \(2020\)](#) estimate applicant willingness to pay for these bear hunting permits in a dynamic discrete choice framework.

and Thakral (2021), study alternative mechanisms to allocate public housing in various cities in the United States and the United Kingdom. We build on this literature in two ways.

We are the first to estimate a model of public housing with a secondary market and nontrivial dynamics. Unlike in rented social/council housing, owner-occupants hold equity in their homes, necessitating dynamic considerations. When deciding which apartment to purchase, putative homebuyers need to account for how their property prices will evolve. Hence, after 5 years, these owner-occupants continually trade off the “option value” of keeping their apartment against the cash they would obtain from selling it off on the secondary market. Since this secondary market exists, in each BTO cycle, an unhoused young couple not only has to decide to which development to apply, but also *whether* to apply at all. “Used” apartments remain attractive to richer households who are impatient or nearing the end of their search. Thus, any policy change in the BTO mechanism may spill over to the secondary market for apartments. Unlike our predecessors, we model this market and show that BTO rule changes can affect owner-occupier home equity by an economically important margin.

Moreover, we find that *rules matter* when considering equivalent changes in supply. Our predecessors find that, in the setting of auctions, the value of negotiating skill may be small relative to inviting one additional bidder (Bulow and Klemperer 1996). Often, design changes are said to improve welfare by an equivalent increase in the supply, for example, of donor kidneys (Agarwal et al. 2021a). In our paper, we qualify this sentiment. How effective is increasing supply? The answer depends crucially on the rules under which this supply is being allocated, as well as the characteristics of the supplied goods.

Our paper is also related to a burgeoning literature on neighborhood choice in Empirical Industrial Organization (see e.g. Bayer, Ferreira, and McMillan 2007; Geyer and Sieg 2013; Galiani, Murphy, and Pantano 2015; Bayer et al. 2016; Almagro and Domínguez-Iino 2019; Van Dijk 2019). We account for geography and study a centralized mechanism, differing from Sieg and Yoon (2020), which models search, queueing and mobility in the market for affordable housing in Manhattan. Unlike in their setting, at the margin, expanding the inflow of affordable housing in Singapore does not seem to impose large costs on existing owner-occupiers.

Furthermore, our paper speaks to demand estimation in general (Berry 1994; Berry, Levinsohn, and Pakes 1995; Greene and Hensher 2003), and in particular the estimation of demand for durable goods (Erdem, Imai, and Keane 2003; Hendel and Nevo 2006; Doraszelski and Pakes 2007; Gowrisankaran and Rysman 2012; Aguirregabiria and Nevo 2013; Gowrisankaran and Rysman 2020), with dynamic implications for market design (see, e.g., Bodoh-Creed, Boehnke, and Hickman 2021). We build on this literature by considering demand over apartment lotteries in the style of Agarwal and Somaini (2018), resulting in an additional nested fixed point (apartment success rates) that we solve for in our counterfactuals. Moreover, relative to Gillingham et al. (2022), who study the market for new and used automobiles, their “primary market” for cars clears by price while ours clears by lottery and wait times. To obviate repeatedly iterating value functions when estimating supply, we exploit finite dependence (Arcidiacono and Miller 2011).

Finally, our paper is directly related to various studies of the Singaporean housing market in the Urban and Transportation Economics literature (Wong 2013; Wong 2014; Diao, Leonard, and Sing 2017; Agarwal et al. 2021b; Lee and Tan 2023). We build on this literature on two fronts: not only do we showcase new data from the Housing and Development Board of Singapore, but we are also the first to conduct a structural estimation of a matching model in this rich setting.

3 Policy Background

3.1 Housing stock in Singapore

In Singapore, 80% of the housing stock is government housing, administered and maintained by the Housing and Development Board (HDB).⁶ Over 80% of resident households in Singapore live in these apartments. During our sample period (2012-2015), the average apartment sold for S\$460,000 on the secondary market, or about 4.6 times the median yearly income of a Singaporean household in that period.

The remaining housing stock is private, with the vast majority (19% of the housing stock) being private apartment complexes known as “condominiums.” These complexes are gated communities with their own facilities, like swimming pools, gyms, barbecue pits, and so on. In July 2012, the median price per square foot of new private apartment sales was S\$1,500; given a 2-bedroom apartment size of 900 square feet, said apartment would go for S\$1,350,000, or 13.5 times a household’s median yearly income.⁷ Meanwhile, non-“condominium” private housing, known as “landed property,” are even more expensive.

In this paper, given that private housing in Singapore is unaffordable to the young households the government wishes to target, we will assume that the private housing market is separate from the market for new and “used” government housing.

3.2 The Housing and Development Board and its objective

Shortly after Singapore took over full internal self-government from the British in 1959, the HDB was established in 1960 to quickly build apartments to house all Singaporeans, the majority of whom lived in slums. The agency successfully built 21,000 apartments within 3 years of its formation, and 54,000 by 1965. Today, the HDB manages “1 million [apartments]… in 23 towns and 3 estates” islandwide (Housing and Development Board 2021a).

The HDB’s stated objective is to provide “affordable, quality public housing and a great living environment where communities thrive.”⁸ The Singapore government views homeownership as

⁶For more details on the HDB, consult <https://www.hdb.gov.sg/cs/infoweb/about-us>.

⁷At the time of writing, one US dollar is worth 1.39 Singapore dollars. For the rest of this paper, we will take the Singapore dollar as our default currency.

⁸In related work, Ferdowsian, Lee, and Yap (2021) investigate optimal supply choices in public housing through the lens of dynamic mechanism design and queuing theory. In their setting, the government prefers to minimize vacancies and wait times, but may weight each outcome differently. Given these different social welfare functions, they characterize conditions under which it is possible to achieve a constrained efficient allocation of apartments, and

a valuable endeavor in its own right. Owning one's home dovetails well with several of the government's social goals: fostering a sense of belonging and responsibility to one's neighborhood, socioeconomic mixing, "reinforcing the family institution" ([Chua 2017](#), p. 85), and so on.

In service of this objective, the Singapore government has to balance several competing concerns ([ibid.](#), p. 96). Chief among its concerns is that it must build enough new, "affordable" apartments to house putative homeowners and the poor. By "affordable," the government means that prices for new apartments in neighborhoods farther away from the city center should not be higher than four times an applicant's median income ([Chin and Chang 2013](#)). On the other hand, the HDB refuses to build "too many" new apartments for two reasons. First, vacant apartments are very costly for the government to hold and allocate ([Mah 2011](#), p. 29). Second, the prices of apartments on the secondary market may fall, hurting the home equity of existing owner-occupiers.⁹ Since Singaporeans hold much of their wealth in real estate, volatility in apartment prices would cast a pall over many households' retirement plans, a scenario the Singapore government seeks to avoid.

In contrast with public housing in the United States (US), where households rent the public housing apartments they are assigned to, over 90% of Singaporean households in HDB flats "own their home." That is, these households have signed a deed giving them the right to live in their assigned apartment for 99 years, and are allowed to sell the apartment on a secondary market after living in it for 5 years.¹⁰

3.3 The Build-to-Order Scheme

In Singapore, many government apartments are first introduced into the housing stock via a process known as the Build-to-Order Scheme (BTO). Introduced in April 2001 and taking place every 2-3 months, the BTO exercise allows potential homeowners to ballot for their preferred neighborhood and apartment size. Applicants apply for BTO as a family unit, typically a married couple. One person in the family unit must be a Singapore citizen, while the other must be at least a permanent resident. Both people must be at least 21 years old and have a combined annual income below a threshold (S\$168,000 as of the time of writing). This threshold is set at roughly the 60th percentile of incomes for young households. Finally, no one in the family unit is allowed to own real estate in Singapore or overseas.

In each BTO cycle, putative applicants observe the developments on offer. Then, they decide whether to apply to one development; take an apartment on the secondary market; or wait till the next BTO cycle. Applicants may choose to wait because reneging on an offered apartment could cause them to lose priority in future application cycles. When young households remain

discuss mechanisms implementing this allocation.

⁹In Singapore, a household can finance its government apartment through its mandatory retirement savings account in the Central Provident Fund ([Chua 2017](#), p. 86).

¹⁰Our paper focuses on the primary market for HDB apartments. For a paper that studies the broader spatial organization of economic activity in Singapore, see [Lee and Tan \(2023\)](#).

unmatched, they typically live with their parents, for cultural and financial reasons.¹¹

After the application phase, the HDB assigns each applicant a queue number, indicating the sequence in which she can select her preferred apartment.¹² At any point, an applicant may withdraw her application and participate in a future cycle. However, as mentioned earlier, this withdrawal is not costless in general. If an applicant is twice chosen to select an apartment but never does so, she loses priority in the BTO process for a year, drastically lowering her chances of “winning” future BTO lotteries.

After all applicants have either selected an apartment or withdrawn their application, HDB will commence construction if 70% of all properties in a development have been allocated. In our sample period, despite some vacancies in developments farther from the city center, all BTO developments have crossed this 70% threshold, and thus have been constructed. In practice, most developments of all sizes are oversubscribed, some by at least 2 to 3 times. These apartments are typically ready for homebuyers to move in within 3 years of the corresponding BTO exercise. To deter arbitrage, the government imposes two restrictions. First, an owner may only sell her apartment after she has lived in it for 5 years. Because their units are small, few owner(-occupier)s rent out their homes.¹³ Second, quotas for second-time applicants to BTO are much smaller than those for first-timers.¹⁴ Thus, once an applicant is housed, she is deterred from selling off her apartment, living in temporary accommodation, and applying for a new BTO apartment.

These apartments are often oversubscribed because they are sold at highly subsidized prices, with the amount of the subsidy decreasing in apartment size. The modal grant awarded is over S\$66,000 of a sticker price of S\$200,000 for a 2-bedroom apartment in a “non-mature town,” an area typically farther away from the city center and with fewer completed apartments; and over S\$50,000 for a similar apartment costing about S\$300,000 in a “mature town.”¹⁵

During our sample period of January 2012 to May 2015, about 69,500 apartments were built and offered at BTO, of which about 60,000 were reserved for “first-timers,” or young households who have never been assigned a BTO apartment. To these developments about 183,000 applications were made, of which about 110,000 were made by first-timers. These first-time applicants

¹¹The three dominant racial groups in Singapore are the Chinese, Malay, and Indians. The typical household structure for these groups is the extended family. Moreover, renting is generally unaffordable and “avoided by citizens”: a 2-bedroom apartment outside the city center costs “more than half of the median salary” (Choo 2021). In 2015, only 23,700 Singapore residents under 35 lived alone or away from their parents. In this age group, at most 30% are married. Thus, the fraction of putative BTO applicants who rent is likely to be minuscule.

¹²To enforce social mixing, there are ethnic quotas for each housing development, i.e. a maximum number of Chinese, Malay and Indian households in each government apartment building. These quotas are enforced at both the BTO stage and on subsequent resale. This aspect of the housing system has been extensively studied in previous work (Wong 2013; 2014). The data from our mechanism do not contain information about each applicant’s race, so we will not speak to equity concerns between ethnicities. Instead, we focus on the government’s tension between encouraging homeownership for young households and maintaining the home equity of existing owner-occupiers.

¹³In 2012, about 2.7% of apartments in Singapore were rented out (Housing and Development Board 2022). These rentals include rentals of whole apartments, as well as that of a bedroom within an apartment. The vast majority of owners do not rent out their homes because their apartments are small. The largest apartment type has three bedrooms in total.

¹⁴For instance, 95% of the apartments in developments in “mature” estates are reserved for “first-timers.” These “mature” estates tend to be more expensive and desirable to live in because they are closer to the city center.

¹⁵We describe the subsidy scheme in detail in Sections A.3 and A.4 in the Appendix.

faced an average oversubscription ratio of 1.91:1, with 5th and 95th percentiles of 0.47:1 and 4.73:1 respectively. At the same time, on the secondary market, about 70,000 transactions were made.

3.4 Information available to household at application

When a putative homebuyer is deciding to ballot for a BTO sales launch, she accesses the sales launch subsection on the HDB website (see Figure 8 in the Appendix for this and all subsequent images). After clicking through to that subsection, she sees the projects on offer, so she learns the price for each apartment size-development pair (top right). Additionally, she can also view a map of the neighborhood for her desired development (bottom left) and the associated site plan (bottom right). The applicant thus has a relatively complete picture of the characteristics and surrounding amenities of the apartment in question.

When the application portal is launched, a putative homebuyer has a one-week window to decide which apartment to apply for. Throughout the process, she can view the “flat supply and applications received” for each apartment option, and can condition her choice on the number of applications received so far. However, she will not know the characteristics of the applicants competing with her for these apartments.

In theory, a rational homebuyer should always wait till the last possible moment to submit her application, since she obtains the most amount of information about the application rates to each apartment option. Moreover, once she has submitted her application, rescinding it is somewhat troublesome: she has to either submit a written request or fill out another application in full before canceling the first. In practice, we see many homebuyers submitting their applications well in advance of the deadline. For instance, in the August 2021 application cycle, 47.5% of all applications to 3-room and larger apartments are made on August 13, despite the application window only closing on August 17.

In this paper, because of data limitations, we will assume all homebuyers submit their applications simultaneously, consistent with the principle of strict dominance outlined above. We note that if one observes the number of applicants on each day of the application window, one may be able to back out applicant types by when they submit their applications, thus allowing inferences on homebuyer attrition and entry. This extension is left for future work.

4 Data

Our data cover the universe of applications in the BTO mechanism, as well as all transactions on the secondary market for HDB housing. To our knowledge, we are the first to observe the universe of applications to and subsequent trade of public housing.

Our main data set contains aggregate applications to all BTO developments between 2010 to 2020. These data were constructed partly through a vendor, and partly through liberal use of the Wayback Machine to scrape historical BTO results from the HDB website.¹⁶ In this data set, each

¹⁶Our data provider is Tealida, an independent researcher collating information on past BTO cycles. These data

observation is a development-apartment size pair (i.e. “product-level data”). We observe sticker prices, the number of units offered (“quantity”) and the number of applications to that product. These data are used to infer applicant demand over developments in each period. In our sample (January 2012 to May 2015), we observe about 110,000 applications to 195 developments over 20 BTO cycles. Table 1 contains the summary statistics corresponding to applications to the BTO mechanism.

As a first step to compute the distances of each development to various amenities, we combine these application data with latitudes and longitudes of each BTO development by calling the appropriate APIs on Onemap.sg, a government mapping portal.¹⁷ The algorithm we used selects the first search result corresponding to each development.

To recover applicant preferences for the resale potential of each apartment, we augment our data with the transaction history of all HDB apartments on the secondary market from 2000 to 2021. Here, each observation is an apartment transaction. We observe the street address of the apartment being transacted; its sale price; its approximate floor level; the number of years left on its lease; the number of rooms it has; as well as the HDB town in which it is located.¹⁸

Finally, to recover applicant preferences for various amenities, we use public data from <http://data.gov.sg>. These data include the locations of all elementary schools, and an indicator of whether each school receives additional funding under the Special Assistance Plan (SAP); the locations of all metro stations; the locations of all supermarkets; and the locations of all “hawker centers,” or open-air food courts selling street food.¹⁹ We compute the distance between each BTO and secondary market apartment and the nearest amenity of each type. More details on data acquisition and processing can be found on the Online Appendix.

For dynamic supply estimation, we collapse the apartment transactions on the secondary market by neighborhood, apartment type and corresponding BTO cycle, then merge in the corresponding apartment stock obtained from the Housing and Development Board. Table 2 displays the summary statistics for the dynamic supply estimation data set.

5 Descriptive Analysis

Before we exposit our model and estimation procedure, we describe the apartments chosen by households and provide evidence for several determinants of apartment demand.²⁰

are validated against historical BTO listings and results using the Wayback Machine (<http://www.archive.org/>). See the Online Appendix for more details on data construction.

¹⁷<http://onemap.sg/>

¹⁸We associate each resale transaction with a (latitude, longitude) pair via programmatically calling the Onemap.sg API with the street address of the apartment, falling back on Google Maps if no results are found on the former portal.

¹⁹School data are from the Singapore Ministry of Education. Transit data are from the Singapore Land Transport Authority. Supermarket and hawker center data are from the Singapore National Environment Agency.

²⁰Additional descriptive analysis can be found in Section A in the Appendix.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Period	195			2012-01-12	2015-05-27
Rooms per apartment	195	3.90769	0.774392	3	5
Quantity	195	307.616	197.637	44.1	1176.4
Applications	195	563.666	578.08	30.305	3034.97
Sticker price	195	3.09324	1.02415	1.505	6.505
Forward resale price	195	3.9447	1.02574	2.07182	7.59
Distance to downtown	195	13.6718	3.69131	4.01692	19.36
Distance to metro stop	195	0.989254	0.396679	0.0616367	1.97208
Distance to SAP school	195	4.31581	2.76348	0.293455	10.397

Table 1: Summary statistics by development in the BTO mechanism between January 2012 and May 2015. Quantities and applications are scaled relative to the supply reserved for and the inferred number of first-timer applicants. All prices are expressed in hundreds of thousands of nominal Singapore dollars. Distances to downtown, the nearest metro stop and the nearest Special Assistance Plan (SAP) school are expressed in kilometers.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
BTO cycle	5239	27.4951	15.5898	1	54
Year	5239	2014.41	3.18921	2010	2021
Apartment type	5239	4.4539	1.10335	3	6
Price	5239	5.17865	1.66824	2.2	10.6015
Quantity transacted	5239	42.0053	46.0015	0.0	403.0
Housing stock	5239	8580.97	7552.4	0	36934

Table 2: Summary statistics of secondary market transactions by (neighborhood, apartment type, BTO cycle) from August 2010 to February 2021. Apartment types in $\{3, 4, 5, 6\}$ correspond to 3-room, 4-room, 5-room and Executive/Multi-Generational housing respectively. All prices are expressed in hundreds of thousands of nominal Singapore dollars.

5.1 Apartments in BTO developments are homogeneous

Apart from their location, apartments built in BTO developments are relatively standardized. This is to ensure that they can be built relatively cheaply. Apartments within a development are primarily differentiated along two dimensions. First, we observe the number of rooms per apartment in each development; see Table 3 for a list of indicative floor areas for an apartment with a given number of rooms.²¹ For apartments with two to four rooms, one room is a living room while the remaining are bedrooms. The notable exception is the five-room apartment, which has a living room, three bedrooms and a dining room. Fittings are standard across apartments.²²

Within a (neighborhood, apartment size, BTO cycle) bin, apartments may differ along some dimensions that we do not observe. For instance, an apartment on a high floor facing a hill is likely more expensive and more desirable than a similar unit on a low floor facing a parking garage. At the application stage, a household only knows the distribution of these unobservable characteristics for each development; she only learns the characteristics of the (remaining) apartments in her choice set after HDB calls her to select one.

The remaining variation between developments boils down to observables: agents observe the distance of each development to downtown, to the nearest metro stop, and so on.

In our main analysis, we will restrict our market to all households choosing between 3-room, 4-room and 5-room units. This is because 2-room units attract a large number of “joint single” households, or are shorter-lease units targeted to the elderly. We focus on the largest demographic group applying to BTO apartments: newly-married couples applying for their first apartment.

Number of rooms in apartment	2	3	4	5
Approx. floor area (m ²)	40	70	90	110

Table 3: Government apartments in Singapore by number of rooms and approximate size.

5.2 Construction costs shift BTO prices

Inputs into construction shift the prices of BTO apartments. In recent years, “higher building costs” have pushed the highest BTO prices “closer to [the] million-dollar mark” ([Elangovan 2022](#)).

One key input into apartment construction is concreting sand, which we will use as a cost shifter in demand estimation. Concreting sand is an essential ingredient in mixtures of cement

²¹We omit one-room apartments (“rental flats”) as they are meant for the poorest households; to our knowledge, these apartments are allocated via a waitlist system akin to those common in the United States (see e.g. [Waldinger 2021](#)). There also exist 3-Gen (4-bedroom) and Executive units which do not fall neatly into the framework above. We classify these larger units as 5-room units because (1) they are few in number and (2) they are targeted for larger families, most of whom would consider standard 5-room flats.

²²These fittings include: lighting, window grilles, built-in kitchen cabinets with an induction hob and cooker hood, a kitchen sink, tap, and dish drying rack, a built-in wardrobe, a water heater and a mirror and toilet roll holder in each bathroom. See for example the [November 2020 BTO offerings for a development in Sembawang](#).

and asphalt. In Figure 1, we display a binned scatter plot of BTO prices against a standardized price index of concreting sand. These BTO prices have been residualized on controls including distances to downtown and to the nearest metro stop. As expected, higher concreting sand prices predict higher BTO prices, all else equal.

In demand estimation, we will instrument for endogenous BTO prices by interacting such cost shifters with the number of rooms of each apartment in the BTO development. Since larger apartments require more concreting sand to construct, when prices of concreting sand rise, prices of larger apartments should rise by a greater amount, all else equal. This specification is validated by regressions in Table 19 in the Appendix.

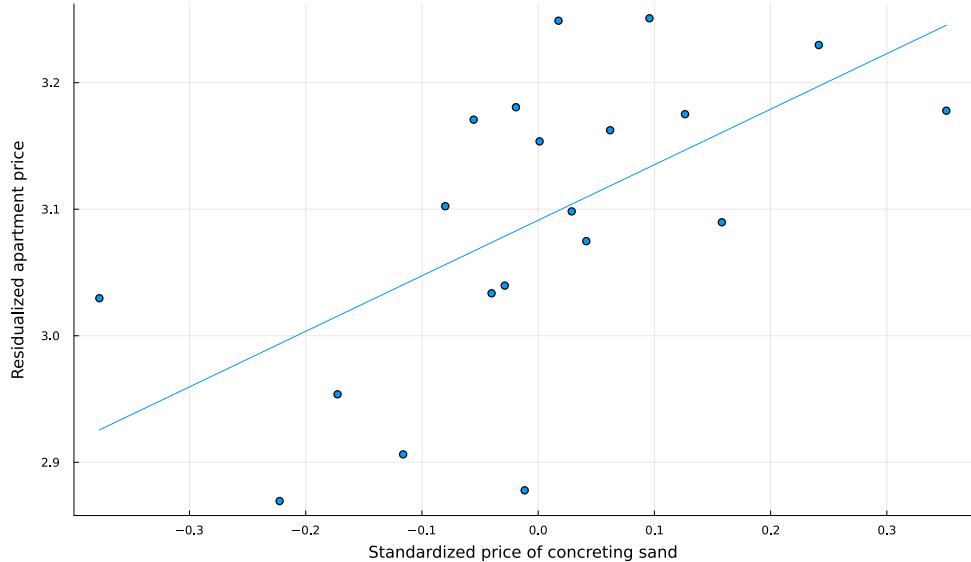


Figure 1: Binned scatter plot of BTO prices against prices of concreting sand, residualized on controls including distances to downtown and to the nearest metro stop.

5.3 Access to (good) schools and public transit

5.3.1 Preferences

For a credible model of BTO applicant demand, we need to control for observable measures of development quality. Such measures include access to downtown, to transit, to good schools, as well as other amenities.²³ In Figure 2, we display binned scatter plots of how oversubscribed BTO developments are, relative to their distance from various amenities. As expected, the closer a development is to downtown, the nearest metro stop or the nearest Special Assistance Plan (SAP) school, the more oversubscribed it is, all else equal. However, there appears to be no relationship between how popular a development is and how far it is from the nearest (ordinary) school. We

²³ Applicants have cited poor amenities as a reason to delay application to the next BTO cycle. In February 2023, Ms. Low Wei Xin [gave] “the current sales exercise a miss” because most of the developments “felt too *ulu* (Singaporean slang for remote)” (Ong 2023).

distinguish SAP from non-SAP schools to proxy for school quality: SAP schools specialize in bilingual education in English and Chinese and are academically competitive.

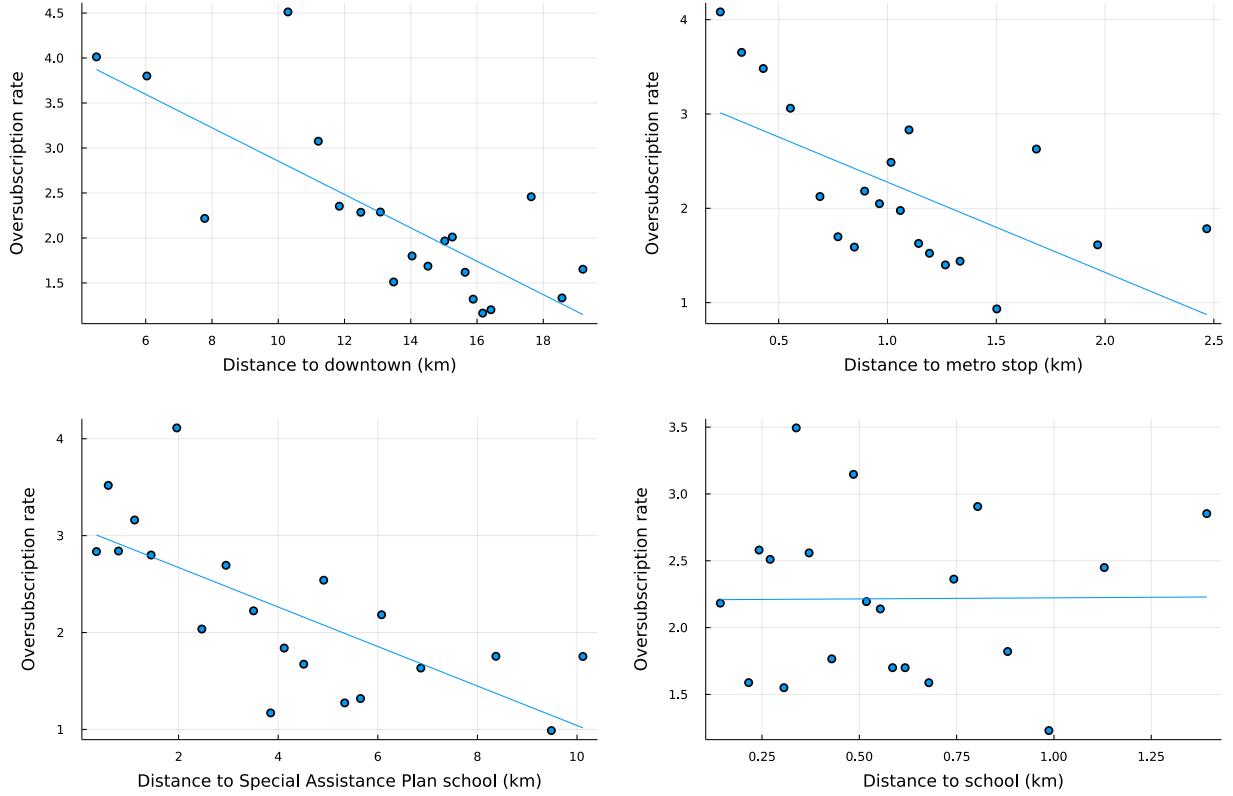


Figure 2: Binned scatter plots of oversubscription rates by development against the distance of said development to various amenities. The oversubscription rate of a development is the ratio of its number of applicants to the quantity supplied. The plotted developments span the January 2012 to May 2019 BTO cycles.

5.3.2 Residential sorting and congestion effects of BTO are small

In our modeling below, we will take the evolution of neighborhood compositions and that of amenities as invariant to our counterfactual simulations. Throughout, we maintain that our counterfactuals do not change the paths of how many singles marry and whether these newly-married couples demand housing *at all*. Then, because of the income eligibility limits and aforementioned racial quotas, government housing neighborhoods are relatively homogeneous by race and income. Thus, endogenous neighborhood composition is not of first-order concern for our purposes.

However, as more residents live in a particular neighborhood, local amenities could become more congested. First, we rule out traffic congestion. Since cars can cost as much as a house, and the transit system covers much of the city, most workers commute by bus, metro, or on

foot.²⁴ Second, we argue that schooling amenities are unlikely to be more congested for small perturbations in apartment quantity. In Figure 3 below, we plot summary statistics, from 2009 to 2021, of the percentage of vacancies in first grade by school. Our two comparison neighborhoods, Ang Mo Kio and Punggol, are representative of mature and non-mature estates respectively. In both neighborhoods, we find mean vacancies per school of about 20%, with interquartile ranges between 0% and 50%. These percentage vacancies have held steady despite school mergers in the past decade. Furthermore, since the Singaporean school system is funded by the national government and cohort sizes were larger pre-2009, schools remain capable of accommodating future rises in local enrollment. Therefore, we do not regard congestion in elementary schools as of first-order concern.

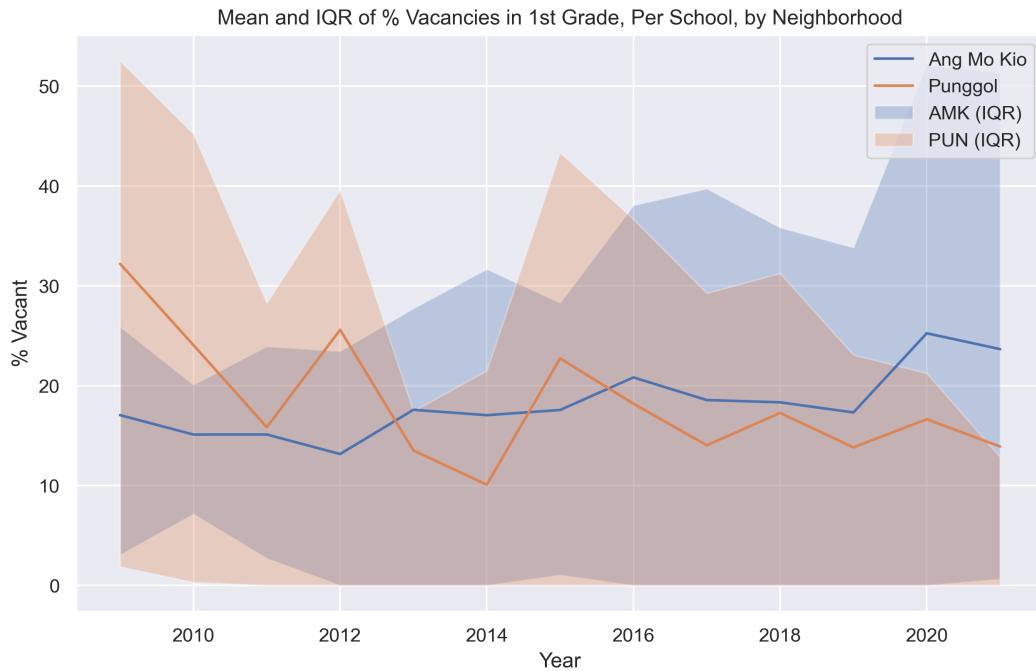


Figure 3: Means and interquartile ranges of percentage vacancies per school by neighborhood by year. Percentage vacancies in a year correspond to the number of vacant places after Phase 2C of the Primary One Registration Exercise in that year. Ang Mo Kio is a representative mature estate (without much new BTO apartment construction) and Punggol is a representative non-mature estate (with planned future BTO construction).

²⁴Commuters rely on taxis and ride-sharing services for occasional late night trips. As of this writing, a Toyota Corolla costs about S\$150,000, or about 1.5 times the yearly income of the median household. On the other hand, transit fares range from S\$0.95 to S\$3.30 per trip, depending on travel distance. See [Lee and Tan \(2023\)](#) for details.

5.4 Households are forward-looking

How do dynamics matter in our setting? Each young household knows the developments on offer both today and in the next cycle; if the developments next quarter are “better” than today’s, a putative applicant may elect to wait and only apply to a development next cycle. Waiting can be rational because renegeing on an offer is costly. If a young household applies to a development today, is invited to select an apartment but turns down the offer twice, she loses priority in the BTO cycles in the coming year.

As we saw in Section 5.3, young households seem to like developments that are closer to the nearest metro stop. If the developments next cycle are closer to the nearest metro stop on average than today’s, more applicants should apply to those developments relative to today’s, all else equal. This stylized fact is displayed in Figure 4. In the left panel, we display a binned scatter plot of oversubscription rates in a BTO cycle against the mean distance to the nearest metro stop of all developments offered in that cycle. In this plot, there appears to be a weak negative relationship between the oversubscription rate in a cycle against the aforementioned mean distance. In contrast, in the right panel, we plot first differences over time in both oversubscription rates and mean distances. In this second plot, if the developments next cycle are farther from a metro stop relative to today’s, we predict that developments next cycle will be less oversubscribed relative to today’s, all else equal. Since the linear fit improves significantly in the second plot relative to the first, we have suggestive evidence that households are forward-looking.

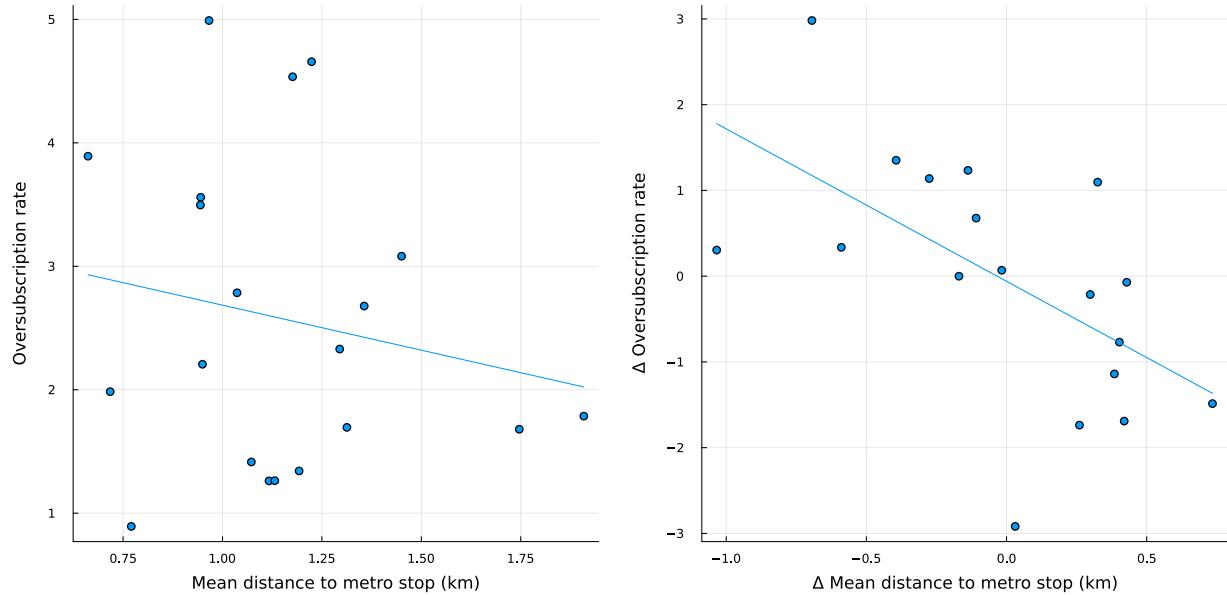


Figure 4: Binned scatter plots of oversubscription rates in a BTO cycle against the mean distance to the nearest metro stop of all developments offered in that cycle. The left panel displays the plot in levels; the right displays first differences in oversubscription rates and mean distances over BTO cycles ($t, t + 1$). The plotted BTO cycles span January 2012 to May 2019.

6 Theoretical Example

Our main design intervention targets inefficiencies from limited choice expression and rational delay. Under the current mechanism, in any one BTO cycle, households are not allowed to list a second development as acceptable to them. Moreover, if next cycle's developments are much more attractive than this cycle's, putative applicants may wait till next cycle and try for a competitive development. Some of these applicants will fail to get an apartment in said development, and experience ex post regret. Rather than remaining unmatched at all, they would have been willing to "settle for" an apartment in the previous cycle.

In Section 7, we will describe a richer model that we can take to the data and from which we can simulate our proposed interventions. For the sake of exposition, in this section, we illustrate key tradeoffs with a simple theoretical example. We abstract from equilibrium in the secondary market and limit our attention to a setup with three agents and two developments of capacity 1. First, we characterize the BTO equilibrium. Next, we demonstrate that, under BTO, building more apartments may be ineffective at reducing vacancies precisely because of rational delay. Finally, we show that if the government adopts a strategyproof mechanism, adding supply achieves its intended effect, matching all agents to an apartment.

6.1 Setup

There are two periods, $t = 1, 2$. In Period 1 (2), one house A (B) arrives. At the end of each period, vacant houses vanish. Three identical players $i = 1, 2, 3$ are born at the beginning of time and are perfectly patient. Every period, each active player i simultaneously takes one of three actions. She can apply for the available house; wait one period; or exit the market. If house j is oversubscribed, the winning agent is chosen via uniform random lottery. Agents who are matched to a house or exit the market stop making further decisions. If an agent waits or otherwise remains unmatched in Period 2, she exits the market.

Agents value house A at 2 utils and B at 5 utils. Unmatched agents between Periods 1 and 2 incur a small waiting cost of $\epsilon \in (0, 1)$. Agents exiting the market in Period 1 (2) receive a payoff of -2 (-1) utils, representing higher housing congestion in earlier periods from a smaller stock of available developments.

6.2 BTO Equilibrium

We seek a Subgame Perfect Nash Equilibrium. We claim that in Period 1, everyone applies to house A; then, in Period 2, the remaining agents apply to house B. Proceeding by backward induction, consider any subgame in which two agents are unmatched at the start of Period 2. It is strictly dominant for each agent to apply to house B, since remaining unmatched yields a negative payoff for sure. Thus, each agent's expected utility at the start of Period 2 is

$$V_2 = \frac{1}{2} \times u(B) + \frac{1}{2} \times u(\text{exit}_2) = 2.5 - 0.5 = 2.$$

Then, any agent left unmatched at the end of Period 1 incurs the waiting cost ϵ , so their expected payoff at the end of Period 1 is $2 - \epsilon$.

At the start of Period 1, we conjecture that everyone applies to house A. As in Period 2, exiting the market yields a negative payoff and is thus strictly dominated by applying to house A. Applying to house A yields a payoff of

$$v_1(a; -a) = \frac{1}{3} \times u(A) + \frac{2}{3} \times (2 - \epsilon) = 2 - \frac{2}{3}\epsilon,$$

whereas waiting yields a payoff of

$$v_1(w; -a) = 2 - \epsilon < v_1(a; -a).$$

Therefore, in Period 1, all agents apply to house A; then, in Period 2, the remaining agents apply to house B.

The resulting allocation of houses is a permutation of $x = (A, B, \emptyset)$. No houses are vacant.

6.3 Under the current rules, building more “B” is ineffective

We show that, under the current rules, added supply can be ineffective. Suppose the government built one more house B, arriving in Period 2. We verify that in the new equilibrium, in Period 1, everyone waits; then, in Period 2, everyone applies for B. Proceeding by backward induction, consider any subgame in which all three agents are unmatched at the start of Period 2. It is strictly dominant for them to apply to B, since remaining unmatched yields a negative payoff for sure. Thus, each agent’s expected utility at the start of Period 2 is

$$\tilde{V}_2 = \frac{2}{3} \times u(B) + \frac{1}{3} \times u(\text{exit}_2) = \frac{10}{3} - \frac{1}{3} = 3.$$

Then, any agent left unmatched at the end of Period 1 incurs the waiting cost ϵ , so their expected payoff at the end of Period 1 is $3 - \epsilon$.

At the start of Period 1, we conjecture that everyone waits. As in Period 2, exiting the market yields a negative payoff and is thus strictly dominated by applying to house A. Applying to house A yields a payoff of

$$\tilde{v}_1(a; -w) = 2,$$

whereas waiting yields a payoff of

$$\tilde{v}_1(w; -w) = 3 - \epsilon > \tilde{v}_1(a; -w).$$

Therefore, in Period 1, all agents wait; then, in Period 2, everyone applies to B.

The resulting allocation of houses is a permutation of $\tilde{x} = (B, B, \emptyset)$. Vacancies rise (house A is empty). Average wait times rise because everyone waits till Period 2.

Two insights can be gleaned from this exercise. The first is the potential for ex post regret.

The unmatched agent prefers to be matched with house A than remain unmatched, even though it was rational for them to try for house(s) B. The second is that vertical quality and intertemporal substitution matter. If houses A and B were of identical quality, no one would have an incentive to wait. Nor would anyone wait if they were sufficiently myopic, e.g. if each agent discounted her payoffs in period 2 by a factor of $\delta = 0.5$. Thus, when we amend the BTO program, dynamics and heterogeneity in developments play a crucial role in driving our results.

6.4 Once we shut down intertemporal risk, adding supply can be effective

Once we shut down intertemporal risk, adding supply succeeds in matching all the applicants. To target this source of inefficiency, we implement a version of Random Serial Dictatorship (RSD) closely resembling the mechanism we simulate in Section 10. The stock of available housing is 1 unit of A in Period 1, and 2 units of B in Period 2. Under the new rules, at the beginning of time, all three agents submit a rank-ordered list over house A and house B. Then, at random, each agent is assigned her highest-ranked option that is still available to her. If an agent is unassigned, she exits either in Period 1 or Period 2, each with probability 0.5.

Since RSD is strategyproof, all agents truthfully specify that they prefer house B to house A to remaining unmatched. The resulting allocation of houses is a permutation of $x' = (A, B, B)$. No houses are vacant. Thus, under the new rules, building more apartments can ease BTO congestion.

Our illustrative model abstracts from equilibrium in the secondary market for apartments. Moreover, it does not capture the rich substitution patterns between developments in the same BTO cycle, as well as between one cycle and the next. To fully capture the equilibria and spillovers from our proposed interventions, we need a model we can take to the data.

7 Model

We expand on our illustrative model to recover the preferences of young households and owner-occupiers of existing apartments. Our demand model closely resembles the decision-making process of each putative BTO applicant, while our supply model captures the tendency for each owner-occupier on the secondary market to “cash in” on higher home values.

Each period, new BTO developments arrive exogenously, each with a fixed number of units. On the secondary market, each owner-occupier decides whether or not to sell their apartment in the time frame corresponding to the prevailing BTO cycle. The trade-off for them is between selling today and selling at a higher price tomorrow. Once she sells her apartment, an owner-occupier exits the market. We interpret “exit” to mean a resident upgrading to private property, or moving in with their children in their old age.²⁵

On the demand side, every BTO cycle, new young households become active for a maximum of $\bar{\tau}$ periods. All young households choose one BTO development to which to apply; wait; or

²⁵See Subsection 7.6 for details.

exit to the secondary market. Their choice depends on their preferences, lottery odds and prices on the secondary market. Matched households obtain their apartment and exit the market.²⁶ Unmatched households of age $\bar{\tau}$ exit to the secondary market at the beginning of the $\bar{\tau} + 1$ -th period in which they become active.²⁷

7.1 Developments offered at BTO

Time is discrete and indexed by $t = 0, 1, 2, \dots, T$. Each time period corresponds to a BTO application cycle. In the BTO mechanism, every period, developments $a = 1, 2, \dots, A_t$ arrive exogenously, each with its respective number of units $Q_{1t}, Q_{2t}, \dots, Q_{At}$. Let \mathcal{A}_t represent the set of developments available at time t . The prices of BTO apartments are set exogenously by the government.

7.2 Model timing

Fix a time period t . Putative BTO applicants have perfect foresight and are finitely-lived. They age deterministically across periods. At the posted secondary market prices p_t^S and BTO success probabilities q_t , on the demand side,

1. Putative applicants in cohort t are born.
2. All agents observe developments $a = 1, 2, \dots, A$ on offer via BTO in that period, as well as the price p_t^S of taking an apartment on the secondary market. For each development a offered at time t , let the quantity of apartments available in that development be Q_{at} .
3. Each household either applies for an apartment in BTO ($a \in \mathcal{A}_t$), exits the mechanism ($a = E$), or opts to wait: ($a = W$).
4. If a household exits the mechanism (i.e. $a = E$), it purchases an apartment on the secondary market and takes no further action. Else if a household has applied to an apartment within the mechanism, it learns if it is matched to its preferred development. Matched households exit the mechanism and collect utility from purchasing their BTO flat. Unmatched and waiting households pay a waiting cost and remain in the market.

²⁶Recall that a young household that purchases a government apartment cannot sell it off until 5 years have elapsed. Since our sample period is shorter than 5 years in length, we assume these (new) owner-occupiers do not take any further action.

²⁷Though we specialize our model to our empirical setting, our approach can be adapted to other instances of dynamic demand over lotteries. For example, our model can be adapted to school and course choice settings that do not utilize First-In-First-Out (FIFO) mechanisms. We give an example of a non-FIFO mechanism, the “Primary One Registration” exercise governing admission into first grade in Singapore. Every admissions cycle, there are several priority phases for children with siblings in the same school, children with alumni parents, and so on. Priority phases take place sequentially. If a child applies to a school under the first priority phase, and the school is oversubscribed in that phase, school places are allocated by uniform random lottery. If the child fails to secure a place in the first phase, she can apply to a different school in the second phase (or the same school), and this process continues until all children are matched. The efficiency of such a mechanism, vis-à-vis deferred acceptance or other centralized assignment systems, remains an open question.

5. Time advances to period $t + 1$.
6. Unmatched agents aged $\bar{\tau} + 1$ in period $t + 1$ exit the mechanism, buy an apartment on the secondary market and take no further action.

Each putative applicant is identified by its (permanent) income type y_i and age $\tau = 1, 2, \dots, \bar{\tau}$. Household income types are drawn from an exogenous distribution \mathcal{F}_y . The aggregate endogenous state of our economy is μ_t , the distribution of alive households by income level and age. The exogenous states are the characteristics of all BTO developments offered at time t .

To simplify estimation, recall that each BTO applicant has perfect foresight over the set of apartments offered throughout the entire history of the mechanism. Hence, the only uncertainty each household faces is over its idiosyncratic preference shocks in each period, as well as whether it is offered the apartment to which it applied.

Simultaneously, on the supply side, owner-occupiers have perfect foresight (through at least 2022). At the posted secondary market prices p_t^S ,

1. She decides whether or not to sell off her apartment.
2. If she sells off her apartment, she exits the market. If she does not, she retains her apartment and time advances to period $t + 1$.

7.3 Supply in the secondary market

On the secondary market, each owner-occupier i lives in an apartment of type l at time t . Every period, she decides whether to sell off her apartment. If she sells, she exits the market. In this case, her indirect utility is

$$w_{i1t|l} = \rho_0 \bar{p}_{t|l}^S + x'_{1t|l} \rho_1 + \xi_{1t|l} + \epsilon_{i1t|l}. \quad (1)$$

That is, her indirect utility depends on the sale price of her apartment $\bar{p}_{t|l}^S$, other covariates $x_{1t|l}$, the unobservable attractiveness of selling $\xi_{1t|l}$ and an idiosyncratic shock to the attractiveness of selling, $\epsilon_{i1t|l}$. We assume that this shock, $\epsilon_{i1t|l}$, as well as its counterpart for not selling, $\epsilon_{i0t|l}$, are independently and identically distributed Type-1 Extreme Valued (T1EV).

On the other hand, if she opts not to sell, her indirect utility is

$$w_{i0t|l} = \delta^0 \mathbb{E} V_{it+1|l}^o + \xi_{0t|l} + \epsilon_{i0t|l}. \quad (2)$$

Let $\bar{w}_{dt|l}$ be the mean utility, aggregated across idiosyncratic shocks $\epsilon_{idt|l}$, of taking action d . Then, the agent's indirect utility depends on her continuation value

$$\mathbb{E} V_{it+1|l}^o = \gamma^E + \ln [\exp(\bar{w}_{0t+1|l}) + \exp(\bar{w}_{1t+1|l})], \quad (3)$$

with γ^E being the Euler's gamma constant; the unobserved attractiveness of not selling $\xi_{0t|l}$; as well as her idiosyncratic shock $\epsilon_{i0t|l}$. Therefore, the market share of sellers of apartments of type

l at time t can be written

$$s_{1t|l} = \frac{\exp(\bar{w}_{1t|l})}{\exp(\bar{w}_{0t+1|l}) + \exp(\bar{w}_{1t+1|l})},$$

and the supply of apartments on the secondary market at time t can be written as

$$Q_t^S(\vec{p}_t^S) = \int s_{1t|l}(p_{t|l}^S) d\lambda_t(l), \quad (4)$$

where λ_t is the measure of housing stock over all secondary market apartment types l at time t .

7.4 Decision problem for eligible BTO applicants

Each BTO applicant faces a dynamic discrete choice problem in her lifetime, specifically in which apartment to apply for each period. We specify household preferences backwards: starting from its decision to accept an offered apartment, then which apartment to apply for. Throughout, fix a time period t and household i of age τ and with income type y .²⁸

7.4.1 Apartment application choice

Consider a household of income level y recently matched to a BTO development a at time t . Then the utility from the apartment she is matched to is

$$U_t(a; y) = x'_{at}\beta^y - \alpha^y p_{at}^y + \alpha^{Ry} p_{at}^R + \xi_{at}. \quad (5)$$

The household likes better apartment characteristics x_{at} but dislikes paying a higher price p_{at}^y . We allow prices to depend on a household's type because poor households receive explicit subsidies that depend on the size and location of the apartment they apply to. Meanwhile, households may also value a higher five-year-ahead resale price p_{at}^{Ry} , as well as the development's unobservable quality ξ_{at} .²⁹

If a household is unsuccessful at obtaining the development she applied for, she pays a waiting cost and continues to the next period, i.e.

$$U_t(0; y, \tau) = -c^y + \delta V_{t+1}(y, \tau + 1), \quad (6)$$

where $-c^y$ is her income-specific cost of waiting and δ is her discount factor.

²⁸Following recommendations in [Andrews, Gentzkow, and Shapiro \(2020\)](#), we discuss alternate model specifications and key channels driving our results in Section H in the Appendix.

²⁹In the mainline specification of our model, we assume beliefs over five-year-ahead resale prices are invariant to our counterfactuals. In our counterfactuals, we implicitly assume that (young households believe that) our rule changes and supply increases do not persist beyond the end of our sample period, May 2015. Since our interventions are temporary, given the government's racial quotas by neighborhood, as well as income restrictions, we do not expect significant differences in long-run neighborhood sorting by race and income. Moreover, the supply increases we consider are minuscule relative to the stock of existing apartments. Hence, in our alternate scenarios, (beliefs over) long-run resale prices are unlikely to differ from the realized path. In robustness checks, we will estimate the relation between forward resale prices vary as a function of current prices on the secondary market, as well as other covariates. Then, we will find a fixed point in success probabilities, secondary market prices, and (beliefs over) forward prices.

If a household exits to the secondary market, she dislikes a higher mean apartment price³⁰ in the time period she is searching over:

$$U_t(E; y) = -\alpha^y \bar{p}_t^S + \xi_t^{Sy}.$$

The term ξ_t^{Sy} is the income-specific unobserved attractiveness of exiting to the secondary market in period t . Meanwhile, waiting households pay a waiting cost and advance to the next period, so their payoff from waiting is is

$$U_t(W; y, \tau) = \xi_{Wt}^y + U_t(0; y, \tau).$$

Similar to exiting, ξ_{Wt}^y represents the income-specific unobserved attractiveness of waiting a period.

We now step backwards to Step 3 and describe the household's decision problem. In each period, she selects a BTO development ($a \in \mathcal{A}_t$), exits ($a = E$) or waits ($a = W$) to maximize expected utility:

$$V_t(y, \tau) = \mathbb{E} \left\{ \max_{d \in \mathcal{A}_t \cup \{E, W\}} \mathbb{E}_t[v_{it}(d; y, \tau) | d, \mu_t] \right\}. \quad (7)$$

The agent makes her choice according to $v_{it}(\cdot; y, \tau)$, her choice-specific value function:

$$\begin{aligned} v_{it}(a; y, \tau) &= q_{at} U_t(a; y) + (1 - q_{at}) U_t(0; y, \tau) + \epsilon_{iat}; \\ v_{it}(W; y, \tau) &= U_t(W; y, \tau) + \epsilon_{iWt}; \\ v_{it}(E; y) &= U_t(E; y, \tau) + \epsilon_{iEt}. \end{aligned}$$

When a household applies to development a at time t , she chooses a lottery where she gets her apartment with probability q_{at} , and is unsuccessful otherwise. Finally, the agent's idiosyncratic shocks $\epsilon_{i,t}$ are drawn iid from a Type-1 Extreme Valued (T1EV) distribution. Let N_{at} be the number of applicants to apartment a at time t .

7.4.2 Applicant state transitions

- If a household chooses to wait, she pays a waiting cost and remains unmatched next period (or, if aged $\bar{\tau}$, is compelled to exit the mechanism).
- If a household takes an apartment on the secondary market, she exits the mechanism.

³⁰For tractability, we capture the indirect utility of exiting to the secondary market by the mean price of an apartment in that period, as well as an unobserved shifter common to all applicants. Implicit in this modeling choice is the assumption that the value of exiting is well captured by the mean price on the secondary market. An alternative approach is to fully model household preferences over each (neighborhood, apartment size) pair offered on the secondary market. For each period t , given a guess of preferences, we can obtain the value of her choice set, then insert this value into the household's choice problem. Unfortunately, this approach suffers from the curse of dimensionality, with the key computational bottleneck being the "middle loop" setting model market shares equal to observed market shares.

- If a household applies for BTO development a , and if $N_{at} \leq Q_{at}$, she is matched to development a with probability 1. Else option a is oversubscribed, so the government selects successful households via a uniform random lottery. With probability q_{at} , the household obtains an apartment in development a . Otherwise, she pays a waiting cost and remains unmatched next period (or, if aged $\bar{\tau}$, is compelled to exit the mechanism).
- If an agent remains unmatched at age $\bar{\tau}$ at time t , she is compelled to exit at time $t + 1$, so her expected utility is

$$V_{t+1}(y, \bar{\tau} + 1) = \gamma^E + U_t(E; y).$$

7.4.3 Market shares

Let $\bar{v}_t(\cdot; y, \tau)$ be the mean utility over all applicants of type (y, τ) taking a particular action. The market share for development a is obtained by integrating over the conditional choice probabilities of each type, i.e.

$$s_{at} = M_t^{-1} \int \frac{\exp(\bar{v}_t(a; y, \tau))}{\sum_{a' \in \mathcal{A}_t} \exp(\bar{v}_t(a'; y, \tau)) + \exp(\bar{v}_t(E; y)) + \exp(\bar{v}_t(W, y))} d\mu_t(y, \tau), \quad (8)$$

where M_t is the number of households active at time t :

$$M_t = \int d\mu_t(y, \tau).$$

7.5 Solution concept

To facilitate estimation, we will make an assumption of large markets. That is, we assume households take success probabilities q_t and secondary market prices \bar{p}_t^S as given. If a household i unilaterally deviates from her equilibrium report σ_{it} , she does not significantly change other agents' success probabilities. Nevertheless, in our counterfactuals, it is important to let application success probabilities q adjust with changing policy regimes.

Definition 1. Let \mathcal{F}_t represent all information available at time t . A **BTO equilibrium** comprises a profile of type-specific strategies $\sigma_t^y = \sigma^y(\mathcal{F}_t)$, secondary market prices \bar{p}_t^S and application success probabilities q_t such that

1. Households behave optimally. Conditional on the realization of household-specific shocks ϵ_{iat}^y , secondary market prices p_t^S and success probabilities q_t , the strategy σ_t^y solves the household optimization problem (7).
2. Application success probabilities are consistent with household choices. Given the strategy profile σ_t^y , the application success probabilities satisfy, for all t ,

$$q_{at} = \min \left\{ \frac{Q_{at}}{s_{at}(\sigma_t^y; q_{at}, p_t^S) M_t}, 1 \right\}. \quad (9)$$

3. Given household behavior and application success probabilities, secondary market prices clear the market for owner-occupied apartments:

$$Q_t^S(\vec{p}_t^S) = s_{Et}(\vec{p}_t^S)M_t.$$

Theorem 1. A BTO equilibrium exists.

We observe that success probabilities q lie in $[0, 1]^{|\mathcal{A}|}$, a compact and convex set. Moreover, mean secondary market prices \vec{p}^S can be constrained to lie in $[0, \vec{p}^{S,\max}]^T$, also a compact, convex set. Furthermore, given preference parameters (β, α, c, ρ) , the mapping from $\omega = (q, p^S)$ to implied success probabilities and excess demand is a continuous function, by the aforementioned large-market assumption and an interpolation procedure. By Brouwer's Fixed Point Theorem (1911), this mapping has a fixed point ω^* .

However, given preference parameters (β, α, c) and the initial conditions on the market size and the distribution of incomes and ages, the resulting lottery odds and secondary market prices $\omega = (q, p^S)$ may not be unique.³¹ This observation does not pose a problem in estimation, since we will recover applicant parameters in the equilibrium played in the data. In counterfactual simulations, we will impose the following equilibrium selection rule: we will start our optimizer at the ω observed in our data. In practice, starting our optimizer at other feasible points does not change our qualitative results.³²

7.6 Model discussion

When the government builds more apartments, two economic forces are at play: Higher supply relieves congestion but the demand response exacerbates it. If apartments were all homogeneous, fixing the flow into the mechanism, building more apartments reduces congestion mechanically. However, in equilibrium, building more apartments in a desirable area may lead to agents switching from their original choice to the “better” development, partially undoing the supply expansion. Since agents are forward-looking, the aforementioned substitution not only happens across space, but also across time. Since eligible agents are always free to wait, they may try for a “better apartment” next period instead of “settling” for an apartment today. This intertemporal substitution is bad for the government in two ways: agents remain unmatched for longer and more apartments remain vacant.

Therefore, which of these forces dominates is an empirical question. Below, we discuss other model assumptions.

³¹We display a simple example of multiple equilibria in our setting. Fix an equilibrium E and a period t . Suppose, in that period, developments A and B confer identical match utilities and are not congested (i.e. have fewer than 1 applicant to 1 apartment). We construct a second equilibrium E' . Let all of the applicants, except for one, behave as in equilibrium E . Let the “deviating” applicant switch from development A to development B (or vice versa). Then equilibrium success probabilities and secondary market prices in E' would remain the same in E , but we obtain a different allocation of apartments to applicants.

³²Other starting points include setting success probabilities equal to 1 for all BTO developments; starting secondary market prices at the mean value during the sample period; and so on.

Large markets. In our model, each agent maximizes her utility, while believing that she cannot influence other agents' success probabilities. We believe this assumption is innocuous because an average of 322 apartments were offered per period per apartment type, with 95% range (98, 888). Similarly, the number of applicants per period per apartment type averaged 978, with 95% range (93, 3239). Therefore a deviation by a household shifts success probabilities by at most 1/93, or less than 1.1%. Nonetheless, this assumption is likely to be more valid for larger developments than smaller ones.

No peer effects other than through ξ . In our model, peer effects cannot enter the applicant's decision calculus other than through a development's unobserved quality ξ . This assumption rules out cases where two households apply to the same development because they want to live near each other's families. From speaking with BTO applicants, we understand that they apply to developments closer to their workplaces and to the nearest metro stop, rather than near where their friends live. This sentiment could be because Singapore is sufficiently small and well connected by transit.

Perfect foresight. Young households are assumed to have perfect foresight over the approximately 2.5 years they remain active. This assumption is valid in our context because of the copious development, neighborhood and pricing information provided by the government.³³ Moreover, the government routinely announces the next year's government apartment supply and neighborhoods well in advance of each BTO cycle. Thus, in practice, agents can foresee the quality of developments at least 4-5 cycles out. We expect a model of agents with limited foresight to deliver the same qualitative predictions as ours.

Owner-occupiers exit after selling their apartment. After an owner-occupier sells off her apartment on the secondary market, we assume that they exit the market and take no further action. Our assumption covers two major cases of movers. First, while some elderly households age in place, many others dispose of their apartments and move in with their children, financing their retirement using the home equity they cashed in. Second, several owner-occupiers experience a high income or wealth shock and elect to move into private housing. However, the structure of our model rules out a third class of movers: residents disposing of their government apartment and purchasing another. Since we only observe apartment transactions, but not who sold to whom, we do not know the precise level of "residual demand" from agents eligible for government housing but not BTO.³⁴ As family sizes fall

³³We assume households can observe all amenities near each (development, apartment size) pair because of the official maps provided by the HDB (see Figure 8 in the Appendix). The HDB also furnishes applicants with approximate prices for each apartment, as well as resale prices of comparable nearby apartments. See, for example, the [HDB news release for the May 2021 BTO cycle](#).

³⁴There are no statistics on movers from one government apartment to another. However, in the 2018 HDB Sample Housing Survey, just under 14% of current residents made "lateral moves," from one government apartment to another of the same size ([Housing and Development Board 2021b](#)). Since the time they were married, 63.6% of residents in government housing made one or fewer move, i.e. into their first government apartment. When asked if they were "content with their [apartment]," between 60% and 75% of residents answered that they were. Hence, lateral movers are not of first-order concern in our setting.

and transit becomes more efficient, we expect this last group to be small relative to the rest of the market.

8 Estimation

With our model, we intend to simulate our policy interventions: changing rules and adding supply. In this section, we recover the preferences of putative BTO applicants and to what extent owner-occupiers move when their homes appreciate. Since (secondary market) supply only relies on data from the secondary market, we estimate supply offline before tackling demand:

1. (Supply.) Use finite dependence to eliminate the value function in an owner-occupier's moving decision. Then, regress adjusted log differences in moving shares on adjusted differences in prices between today and the next BTO cycle.
2. (Demand.) Recover BTO applicant preferences via the Generalized Method of Moments (GMM), conditioning on the observed success probabilities and prices. The shares of each development, as well as exiting, are matched exactly. Then, we minimize an IV-GMM criterion.

8.1 Secondary market supply

We estimate supply on the secondary market by exploiting finite dependence ([Arcidiacono and Miller 2011](#)). Specifically, an owner-occupier exits the market once she has sold her apartment. Thus, no matter whether she sells off her apartment today or tomorrow, her continuation value "cancels out," allowing the econometrician to collapse a dynamic problem to a static one.

Our model is identified off variation in mean sale prices of each apartment type over time and in space, vis-à-vis variation in the shares of movers and stayers in each (neighborhood, apartment size) in each quarter. The model "corrects" for forward-looking behavior by leveraging one-period-ahead mover shares of the corresponding apartment type.

Fix an apartment type l and a time period t . Using the Hotz-Miller (1993) inversion, we take log differences between the share of movers and that of stayers. Then, the relative attractiveness of selling, against not selling, is

$$\ln s_{1t|l} - \ln s_{0t|l} = \bar{w}_{1t|l} - \bar{w}_{0t|l} = \rho_0 \bar{p}_{t|l}^S + x'_{1t|l} \rho_1 - \delta^o \mathbb{E} V_{t+1|l}^o + \xi_{1t|l} - \xi_{0t|l}. \quad (10)$$

In our model, selling one's apartment is a terminal action, so the inclusive value at time $t + 1$ can be written as

$$\mathbb{E} V_{t+1|l}^o = \gamma^E + \rho_0 \bar{p}_{t+1|l}^S + x'_{1t+1|l} \rho_1 + \xi_{1t+1|l} - \ln s_{1t+1|l}.$$

Substituting this inclusive value term into Equation (10), we obtain

$$\begin{aligned} \ln s_{1t|l} - \ln s_{0t|l} - \delta^o \ln s_{1t+1|l} &= -\delta^o \gamma^E + \rho_0 (\bar{p}_{t|l}^S - \delta^o \bar{p}_{t+1|l}^S) \\ &\quad + (x_{1t|l} - \delta^o x_{1t+1|l})' \rho_1 + (\xi_{1t|l} - \xi_{0t|l} - \delta^o \xi_{1t+1|l}). \end{aligned} \quad (11)$$

We are interested in ρ_0 , which governs the responsiveness of an owner-occupier's moving decision to changes in their apartment's price. This parameter can be recovered by forming the composite regressors on the left- and right-hand sides of Equation (11), then running a regression with fixed effects for each apartment's neighborhood and its number of rooms.

A concern in our setting is omitted variable bias (OVB) in ρ_0 . The composite unobservable term

$$\tilde{\xi}_{t|l} = \xi_{1t|l} - \xi_{0t|l} - \delta^o \xi_{1t+1|l}$$

may contain terms jointly affecting sale prices and the propensity of each owner-occupier to move. For instance, during the COVID-19 pandemic, owner-occupiers are less able to search for new homes and value their existing living arrangements more. In this example, these homeowners will demand a higher price before they are willing to move, and the share of movers will fall.

To mitigate the effect of OVB, we will instrument for prices with (demand-side) policy shocks in August 2015, July 2018 and August 2019. In 2015 and 2019, the government unexpectedly raised subsidies and expanded eligibility for applicants to the BTO mechanism. Unmatched households would thus value applying to BTO over taking an apartment on the secondary market, resulting in a negative demand shock to the latter. In 2018, the government unexpectedly tightened borrowing limits on residential property by 5%, resulting in a negative demand shock over all housing.³⁵ For our instruments to be valid, the aforementioned shocks must be correlated with sale prices but not with the composite unobservable $\tilde{\xi}_{t|l}$. We believe this exclusion restriction is valid because the timing and magnitude of these policy changes could not have been anticipated by the owner-occupiers.

8.2 Demand

We use the Generalized Method of Moments (GMM) to estimate the demand for apartments, as described in [Hansen and Singleton \(1982\)](#). We recover preferences and waiting costs associated with the two latent types in our model, corresponding to low- and high-income applicants respectively.

Our estimation process involves a doubly nested fixed point procedure consisting of three loops, similar to that of [Berry, Levinsohn, and Pakes \(1995\)](#). We extend their estimation method to handle dynamics and choice over lotteries. We begin by conditioning our estimation on prices

³⁵To curb speculation on the market for private housing, the Monetary Authority of Singapore (MAS) mandated that the maximum Loan-to-Value (LTV) limits on individual borrowers be lowered from 80% to 75% on first housing loans in general. If the tenure of the loan exceeded 30 years or extended past the borrower's 65th birthday, the corresponding LTV limits also fell from 60% to 55%. See [the corresponding MAS news release](#) for more details.

and success probabilities observed in the data. In the innermost loop, given these observed data, a guess of parameters, and a guess of the mean utility of each development, we solve the dynamic program for each type of applicant. This loop allows us to calculate the model-predicted choice probabilities over each development, waiting, and exiting. In the middle loop, we find mean utility parameters that set model-predicted market shares equal to the observed shares. Having found the “correct” mean utility parameters that match observed and predicted shares, we form an IV-GMM criterion. This criterion function imposes orthogonality between the mean utilities of each development and the instruments. Finally, in the outermost loop, we search over nonlinear parameters to minimize the criterion function.

In this section, we first outline an informal identification argument. Next, we describe the GMM estimation problem. Then, we describe the instruments used to form the associated moment conditions. Finally, we specify other calibrated quantities necessary for estimation.

8.2.1 Identification of demand in practice

Identification for the demand model follows standard arguments in [Berry and Haile \(2014\)](#). The key threat to identification is that developments are attractive in ways that we do not see. Hence, in the GMM criterion, we need instruments that shift demand but not through the unobserved attractiveness of each development. To instrument for endogenous prices and success probabilities, we employ cost shocks, a policy change affecting only secondary market supply, and differentiation IVs.³⁶

Given mean utilities $U_t(a)$, variation in each regressor identifies its corresponding coefficient in the indirect utility expression. Moreover, there are several developments at which agents will be successful with probability 1, so wait costs do not enter the indirect utility of applying to these developments. Thus, since the mix of developments offered varies from period to period, we can separately identify the level of indirect utilities and wait costs. Finally, variation in one-period-ahead values affects parameter estimates through contemporaneous market shares. A higher inclusive value tomorrow tilts today’s applications towards apartments with lower success probabilities but higher indirect utilities.

How are random coefficients on price and wait costs identified? We leverage variation in the BTO subsidy scheme: Poor households are subsidized the most for smaller apartments in “non-mature” estates far from the city center, and these subsidies decline if applicants select larger apartments or developments in “mature” estates closer downtown.

Suppose for now that poor households were unsubsidized, and consider a comparative static in which these subsidies gradually “rose” to their true levels. At the outset, our model would predict that poor and rich households have the same coefficients on price and wait costs. As poor households become more and more subsidized, they tilt their applications towards developments with smaller apartments in “non-mature” estates. If all such developments are unexpectedly unpopular, the model rationalizes this phenomenon by lowering how sensitive the poor are to

³⁶Further details on our instruments are available in Subsection 8.2.3.

sticker prices. Furthermore, suppose that in three consecutive BTO cycles, $(t, t + 1, t + 2)$, we see many applications to the aforementioned developments in periods t and $t + 2$, but not in period $t + 1$. Then the model predicts that many poor households must have waited in period $t + 1$, implying lower waiting costs for the poor relative to the rich.

8.2.2 Estimation procedure

Our estimation procedure is two-step optimal GMM. Formally, the estimation problem is:

$$\begin{aligned} \min_{\theta} \quad & g(\xi; \theta)' W g(\xi; \theta) \quad \text{s.t.} \\ & g(\xi; \theta) = Z\xi(\theta) \\ & \xi(\theta), V(\theta) \in \{\tilde{\xi}, \tilde{V} : s(\tilde{\xi}, \tilde{V}; \theta) = \hat{s} \text{ and } \tilde{V} = \mathbb{T}(\xi; \theta)\tilde{V}\}. \end{aligned} \quad (12)$$

In each GMM step, we minimize the GMM quadratic form with associated weight matrix W . The moments $g(\xi; \theta)$ are the inner product of the instruments Z and the recovered unobserved development qualities $\xi(\theta)$. These unobservables $\xi(\theta)$ are chosen, via a Newton root-finding procedure, to set predicted market shares $s(\xi, \cdot; \theta)$ equal to actual market shares \hat{s} . Finally, in the “innermost” loop, the value function V is iterated (via the Bellman operator \mathbb{T}) until convergence. See Appendix D for computational details.

In the next subsection, we describe the instruments Z with which we formed the aforementioned moment conditions. Then, we specify the income distribution, initial market size and age distribution, and other calibrated parameters.

8.2.3 Instruments

Our moment conditions rely on unobserved development quality ξ being uncorrelated with our instruments Z . Moreover, to identify the effect of price on demand, these instruments must affect prices and shift demand (but not through ξ).

We use three sets of instruments:

1. (Cost shifters.) For each development, we interact the contemporaneous prices of granite and concreting sand with the number of rooms in each apartment in that development. These cost shifters are relevant because granite and concreting sand are inputs into production. More granite and concreting sand are used to construct larger apartments; hence, when granite becomes more expensive, the cost to build a larger apartment should rise by more than that of a smaller apartment, all else equal. The exclusion restriction requires that prices of raw materials be plausibly uncorrelated with unobserved development amenities.
2. (Unanticipated stamp duty shock in January 2013.) We include a dummy for BTO periods on and after January 2013, in which the Singapore government raised Additional Buyer

Stamp Duty (ABSD) rates for Singaporeans purchasing their second and subsequent residential properties. Since BTO applicants must have no other property to participate in the mechanism, they are not directly affected by this policy change. However, at the margin, the owner-occupiers “upgrading” to private property are more likely to dispose of their existing government apartments before purchasing private property. Thus, the ABSD rate changes constitute an unexpected supply shock that is plausibly uncorrelated with unobserved development amenities.

3. (Differentiation IVs.) Finally, we construct differentiation IVs (Gandhi and Houde 2021) using the following procedure. First, we predict contemporaneous prices using a flexible function of the aforementioned instruments and other observables. Then, we construct quadratic terms exploiting the isolation of each development j in predicted prices and exogenous observables k , as well as cross terms over different dimensions k and k' .³⁷

Instrument exclusion requires that, with respect to its contemporaneous alternatives, the isolation of each development in characteristics space is uncorrelated with its unobserved quality. This exclusion restriction is plausible because, each period, the government offers a mix of developments across neighborhoods to cater to a wide range of applicants. The main constraints limiting which developments can be offered each period include site readiness, town planning, and bureaucratic approvals that are beyond the purview of the Housing and Development Board.³⁸ Thus, the isolation of each development in its distance to downtown, to the nearest metro stop, and other such characteristics is unlikely to systematically vary with the unobserved quality of said development.

8.2.4 Income distribution

For our two income types, using the 2013 Household Expenditure Survey, we discretize the income distribution for 25 to 40-year olds who are eligible to apply for BTO housing. We impute that 20% of households are poor, with a mean income level of S\$36,000 a year; the remaining 80% are rich, with a mean income level of S\$72,000 a year.³⁹ We assume two income types for tractability; with continuous distributions for random coefficients over price and wait times, solving the nested fixed point problem is computationally infeasible.

³⁷We describe the construction of these instruments in Appendix E.

³⁸In a recent parliamentary question, the Singaporean Minister for National Development wrote that “Since May 2011, HDB has called for and awarded the construction tenders for the vast majority of BTO projects ahead of the outcome of the flat selection... However, how early the construction tenders can be launched depends on a variety of factors, such as readiness of sites, status of the planning approval and design development process, among others” (Lee 2022).

³⁹The income level of the rich households is not important to our analysis, since these households earn too much to be given any explicit subsidies under the 2011-2015 regime. In robustness checks, varying the calibrated income level for the poor does not change our qualitative results.

8.2.5 Market size and an agent's birth-death process

Now, we discuss market sizes and each agent's birth-death process. First, we assume each agent searches for a maximum of 10 periods, or two and a half years. We set $\bar{\tau}$ to 10 to strike a balance between capturing each agent's forward-looking behavior and reducing the complexity of the state space.⁴⁰

Next, we assume that BTO applicants are responsible for 30% of the transactions on the secondary market. We believe that demand on the secondary market is largely driven by households who are ineligible for BTO and cannot afford private apartments or houses; thus, they are likely less sensitive to prices than agents who are eligible for BTO. Hence, we assume that this residual demand is invariant to our counterfactuals.

Then, we need to specify the inflow of new applicants in each period. We assume that about 4,000 new households are born each period, split 20:80, i.e. 800 poor and 3,200 rich. This number arises if the government builds housing at approximately the rate that new households enter.

Finally, we need to specify, at $t = 1$, the market size M_1 as well as the age and income distribution of active applicants μ_1 . These values are obtained implicitly by estimating the model twice.⁴¹ First, we assume 16,000 households were active at the beginning of our sample; these households are 20% poor and 80% rich; and their ages decay exponentially.⁴² We call these initial conditions Init. Next, we estimate the model assuming (M_1, μ_1) are the true initial conditions, obtaining unobserved development qualities $\hat{\xi}_0 \sim \hat{F}_{\xi}$. Then, we match the development characteristics in the 5 periods preceding our sample with the "closest" sequence of 5 periods within our sample. Finally, we append the matched sequence to the beginning of the sample and redraw the unobserved development qualities $\tilde{\xi}_{jt}$ for the matched sequence from the first-step empirical distribution \hat{F}_{ξ} . Holding these draws $\tilde{\xi}_{jt}$ fixed, we re-estimate the model with the augmented sample, now assuming that the initial conditions at the beginning of said sample are Init. Further details are available in Appendix F.

8.2.6 Other calibrated parameters

We describe our remaining calibrated parameters. We maintain our assumptions that all households have the same priority, and the applicants cannot affect the success probabilities of other agents significantly by applying to a different apartment. We also calibrate the annual discount factor to the standard value of 0.96.⁴³

⁴⁰Most households who participate in BTO are matched in very few tries: the "mean number of attempts by [successful] first-timer families... is 1.3" (Lee 2021). Varying the maximum number of search periods $\bar{\tau} \in \{8, 12\}$ does not change our qualitative results.

⁴¹We augment the data because we see the development characteristics before our sample period, but we do not see the number of applicants with the correct priority level, i.e. "first-timers."

⁴²We chose the value of 16,000 because this number of Singaporean couples between the ages of 25 and 40 were first married within a 2.5-year window corresponding to $\bar{\tau} = 10$. In robustness checks, varying the initial market size $M_0 \in \{15000, 17000\}$ does not change our qualitative results.

⁴³In robustness checks, varying the discount factor $\delta \in \{0.9, 0.98\}$ does not change our qualitative results.

9 Parameter Estimates

Having discussed our estimation procedure, we now report our parameter estimates. First, we report the price sensitivity of the owner-occupiers on the secondary market. Next, we discuss the young households' preference parameters and wait costs we recovered in our GMM procedure. Finally, we present several measures of model fit and overidentification checks.

9.1 Parameter Estimates — Supply

We estimate this regression offline. Our data span all secondary market transactions during the 2010-2020 BTO cycles. We drop pairs of observations in which either no sales were observed at times t or $t + 1$ for a given apartment type l . As is typical in the literature, we assume an annual discount factor of 0.96.

The regression results can be found in Table 4. We include fixed effects for each neighborhood and the number of rooms in each apartment. In our preferred specification (4), we find a price coefficient $\hat{\rho}_0$ of 0.712, significantly different from zero at the 5% level. This price coefficient maps to a mean price elasticity of supply of 3.64. Our elasticity is substantially higher than similar measurements in prior work, including the mean across American cities of 1.75 ([Saiz 2010](#)) and the mean census tract-level housing unit provision elasticity of 0.3 ([Baum-Snow and Han 2021](#)). However, we caution that our estimated elasticity is not directly comparable with its counterparts. While our predecessors analyze static housing provision, we model our owner-occupiers as forward-looking and responding to the path of future housing prices.

	(1) LHS (O)	(2) LHS (O)	(3) LHS (O)	(4) LHS (O)
Sale price (S\$100k)	0.011 (0.035)	0.012 (0.035)	0.710** (0.309)	0.712** (0.310)
Estimator	OLS	OLS	IV	IV
Neighborhood FE	N	Y	N	Y
Size FE	N	Y	N	Y
N	4,843	4,843	4,843	4,843
First-stage F	-	-	11.99	11.96

Table 4: Table of results for the secondary market regressions. Standard errors are heteroskedasticity-robust. The first two specifications are ordinary least squares (OLS) regressions of adjusted mover shares on prices, while the last two are IV regressions, instrumenting for endogenous prices with BTO eligibility changes in 2015 and 2019, as well as a shock to the maximum loan-to-value ratio in 2018. The second and fourth regressions include fixed effects for each neighborhood and apartment type.

9.2 Parameter Estimates — Demand

After estimating supply offline, we tackle demand. We estimate our model for the January 2012 to May 2015 BTO cycles, restricting random coefficients to be on wait costs and BTO sticker prices.⁴⁴ We restricted our sample because later periods may not have available five-year-ahead resale prices; moreover, in August 2015, there was an unexpected policy change.⁴⁵ Our results are presented in Table 5. Mean utilities depend on

- the distance to the Marina Bay Financial Centre, a proxy for proximity to downtown;
- the distance to the nearest Mass Rapid Transit (MRT) station, a proxy for transit connectivity;
- the distance to the nearest SAP school;
- apartment sticker price; and
- a “forward resale price” term, proxied for by the five-year-ahead resale price of similarly-sized apartments in the same neighborhood of the development in question.⁴⁶

Our results are consistent with our stylized findings. Transit connectivity and distance to downtown are important factors, as are the apartment size and sticker price. We compute the willingness for each income type to pay for various amenities in Table 6, finding that the rich are more willing to pay for transit access and especially to be closer downtown. To assess the plausibility of our willingness-to-pay (WTP) estimates, we attempt to convert them into Singapore dollars per month. Since each BTO apartment must be held for 5 years before it can be sold off, if we divide the WTP value reported in our table by 60, we obtain the “monthly user value” of the amenity in question. As an example, the poor appear to value living 100 meters closer to a metro stop at S\$35/month, while the rich value the same amenity at about S\$142/month. This could be because the rich more are likely to work in knowledge-intensive industries, which are currently clustered downtown. Moreover, the rich are more likely to travel longer distances for work and play, while the poor are less likely to enjoy leisure activities outside of their immediate vicinity.⁴⁷

⁴⁴We limit the number of random coefficients we estimate because of power concerns — we only have access to “development-level demand.” We are currently requesting data from the Central Provident Fund of Singapore to obtain income and family sizes of matched households, allowing us to estimate a richer model.

⁴⁵See Subsection A.3 in the Appendix for more details. It is difficult to incorporate the August 2015 policy change “in sample” because richer agents became eligible for BTO housing, necessitating a third income type we must track, among other computational burdens.

⁴⁶We included resale prices five years ahead because those prices are realized at the earliest time at which the household is legally allowed to sell its apartment off. Our other covariates were chosen because government officials and participants in the mechanism viewed them as important. See Appendix C for more details.

⁴⁷The fares for a bus and subway trip scale with distance. With a transit farecard, each trip costs a minimum of S\$0.92 and rises to S\$2.77 (see the [Public Transport Council website](#) for a detailed breakdown of Singaporean public transit fare structure). In contrast, taxis and platform ride-hailing services are much more expensive. Thus commuters are likely much more reliant on bus and rail than taxis and private car services. Moreover, our WTP results corroborate the findings in [Lee and Tan \(2023\)](#), who show that the construction of a new subway line may help the rich but hurt the poor in the long run. They find that rich households choose to shop downtown, so service-intensive sectors relocate away from the suburbs, extending commute times for the poor.

Parameters	Estimate	S.E.
Constant	-2.698***	1.050
Distance to downtown	-0.143***	0.0470
Distance to metro stop	-0.729***	0.163
Distance to SAP school	0.0291	0.0389
4-room flat	1.987***	0.305
5-room flat	1.426***	0.499
Price	-0.855***	0.291
Resale price	0.569**	0.232
Subsidized development price	-3.433**	1.373
Wait cost (Poor)	-1.972***	0.346
Wait cost (Rich)	-2.611***	0.202
N	195	

Table 5: Table of results from estimating Equation (12). “Subsidized development price” is the price of an apartment in the development, net of explicit subsidies to the poor. Standard errors are from the GMM procedure. Asterisks indicate significance at various levels (*: 10%; **: 5%; ***: 1%)

Amenity/Value (S\$)	Poor	Rich
Living 100m closer to...		
Downtown	400** (200)	1,600*** (400)
Subway Stop	2,100** (1,000)	8,500*** (2,500)
Wait cost (per person per month)	9,600* (5,400)	50,900*** (18,400)

Table 6: Table of willingness to pay (WTP) for several amenities, in equivalent discounts on an apartment in the BTO mechanism. For each income level, WTP is computed by dividing the estimated coefficient on the corresponding amenity by the estimated price coefficient on inside apartments. Standard errors in parentheses are computed by applying the Delta method to the variance-covariance matrix from the estimation of Equation (12). Asterisks indicate significance at various levels (*: 10%; **: 5%; ***: 1%)

9.3 Model fit

To see how well our demand model fits the data, we display several targeted and untargeted moments in Table 7. Associated binned scatter plots can be found in Figure 12 in the Appendix. These targeted moments cover amenities valued by households, while the untargeted moments validate that there is unlikely to be a time trend or schooling amenity captured by unobserved development quality; moreover, the application behavior implied by our model is consistent with figures brought up in the Singapore parliament.

First, we inspect the distribution of unobserved development qualities ξ .⁴⁸ The GMM algorithm successfully matches (among others) three targeted moments: ξ should be of mean zero and uncorrelated with the distances of each development to downtown and the nearest metro stop.

Turning to untargeted moments, we note that unobserved development qualities ξ are uncorrelated with the BTO cycle in which it is offered, as well as the distance of said development to its nearest school. Thus, ξ is unlikely to capture a time trend or unobserved schooling amenities. Our final untargeted moment is the percentage of agents making three or fewer applications. The Singapore Ministry of National Development (MND) notes that most young households applying for apartments in non-mature estates “are able to book a flat... on their third try” (Wong 2017b). In simulations detailed in Section 10.1, we find that 90% of agents make 3 or fewer applications, which is congruent with the MND report.

Targeted Moment	Target	Value (S.D.)	Untargeted Moment	Target	Value (S.D.)
$\mathbb{E}[\xi_{at}]$	0.0	-0.03 (1.44)	$\mathbb{E}[\xi_{at} \cdot t]$	0.0	-0.81 (20.54)
$\mathbb{E}[\xi_{at} \cdot d_{MBFC,at}]$	0.0	-0.82 (16.57)	$\mathbb{E}[\xi_{at} \cdot d_{school,at}]$	0.0	-0.03 (0.94)
$\mathbb{E}[\xi_{at} \cdot d_{MRT,at}]$	0.0	-0.09 (1.20)	$\mathbb{E}[\mathbb{1}\{\# \text{ apps} \leq 3\}]$	>50%	90%

Table 7: Table of targeted and untargeted moments in the GMM estimation of young household demand. Distances to downtown, the nearest metro stop, and the nearest school are in kilometers. For each moment, where applicable, the standard deviation over all observations is reported in parentheses beside the value of said moment. The percentage of agents with 3 or fewer applications is computed by simulating applicant behavior in our baseline counterfactual.

10 Counterfactuals

10.1 Alternative policies

With parameter estimates in hand, we can now simulate alternative policies targeting key weaknesses of the BTO mechanism. Given the government’s stated objectives, we will evaluate these policies on apartment vacancies, applicant wait times, and prices on the secondary market.

⁴⁸A histogram of unobserved development qualities ξ is displayed in Figure 11 in the Appendix.

Policy	Intervention
Change rules	Allocate by random serial dictatorship
Add supply	Build 10% more in oversubscribed developments
Combined	Change rules + Add supply

Table 8: Summary of counterfactual policies.

The first of these alternate policies is to change the rules of the mechanism to eliminate intertemporal risk. Under the current mechanism, if young households try for an oversubscribed development this period and fail, they cannot go back in time and “settle for” a previously offered development. To mitigate this risk, we will implement a strategyproof benchmark, akin to a dynamic version of Random Serial Dictatorship (RSD). At the given prices, let applicants truthfully declare their preferences; then, draw household priorities at random and assign households to their preferred developments/period of exit. To compute this counterfactual, we solve for the new equilibrium. Equilibrium prices must set excess demand for apartments on the secondary market to zero.

There are two main computational challenges in this procedure: computing household preference lists and solving for prices that clear the secondary market. We sketch the mechanism below:

1. Given prices on the secondary market, applicants truthfully declare their preferences over all apartments over which they are eligible, as well as exiting to the secondary market. For an applicant of type (y, t_0) , where t_0 is her birth period, she is eligible for all developments in periods $t_0, t_0 + 1, \dots, t_0 + \bar{\tau} - 1$, and she can exit in periods $t_0, t_0 + 1, \dots, t_0 + \bar{\tau}$.⁴⁹
2. The PHA draws household priorities at random and assigns households to their preferred developments (or exiting, if applicable).

The simulation algorithm searches over prices on the secondary market until excess demand for those apartments is zero.⁵⁰

We showcase this alternate mechanism because it has two attractive properties. First, this policy completely eliminates intertemporal risk. Additionally, this mechanism is strategyproof: It is a dominant strategy for BTO applicants to report their true preferences. Hence, when finding secondary market-clearing prices, it suffices to recompute agent preferences once. Then, we can simulate many realizations of allocations from the mechanism given each draw of agent priorities, simplifying the computation of excess demand on the secondary market.⁵¹

⁴⁹Despite wait costs, in our simulations, a young household who fails to get her preferred developments may not want to exit immediately. This behavior is driven by two factors. First, secondary market prices may fall in the near future, so a sufficiently patient agent may wait to exit in a later period. Second, an applicant may have a high idiosyncratic utility draw for waiting today, leading her to exit tomorrow.

⁵⁰Details are available in Appendix G.1.

⁵¹However, our proposed mechanism also has a drawback: the government has to run the assignment “once and for all” at the start of the sample period, accounting for all potential entrants. To avoid this drawback, the planner

The second alternate policy directly targets housing scarcity: building more. To operationalize this policy, we increase the quantity supplied in oversubscribed developments by 10%. We only consider increasing supply by a small amount to abstract from changes in equilibrium prices and quantities in the forward resale market.⁵² Doing this requires two substantive assumptions. First, changing apartment supply must not significantly shift patterns of demand and supply for local amenities. Second, patterns of residential sorting must remain invariant under the counterfactual scenario. We argue that, in our setting, both assumptions are reasonable. Residential sorting is plausibly invariant because the government imposes (binding) racial quotas in each block of public housing, and balloting for new apartments is limited to households below an income threshold. Furthermore, most neighborhoods in Singapore see their housing stock grow by under 5% per year. If we limit our counterfactual supply expansion to about 10% per development, then each neighborhood sees a further increase of 0.5% relative to the baseline, which we argue is not of first-order consequence.

To find a new equilibrium when more apartments are built, recall that we need to find success probabilities q and secondary market prices p^R such that, at the prevailing prices, the success probabilities q are self-fulfilling; and, at the given success probabilities, the secondary market clears at the prevailing prices. Computational details, as well as notes on equilibrium existence and uniqueness, are available in Appendix G.2.

10.2 Outcome comparisons

To assess the efficacy of each counterfactual in terms of efficiency and equity, we compute three sets of summary statistics:

could consider a version of the “common lottery” (Shi and Yin 2022). Upon their first entry in the mechanism, each household is assigned a persistent lottery number. With this lottery number, each quarter, agents apply for at most one BTO development, and are assigned apartments based this lottery number. Under perfect foresight over future developments and knowledge of the equilibrium success probabilities at each development, this new mechanism also eliminates intertemporal risk. While the “common lottery” places great burdens on what the decision maker needs to know and anticipate, this alternate mechanism can be implemented and can accommodate priorities based on income or household size. We will investigate the “common lottery” mechanism, adapted to our context, in future work. Ideally, given infinite computational power, we would prefer our agents to specify their preferences *period-by-period* over offered developments, exiting, and waiting. Unfortunately, we are cursed by dimensionality. For us, this alternate approach entails three computationally-intensive loops. Given a guess of secondary market prices and the value of waiting, we must compute preference lists and simulate assignments. From these assignments, we can obtain an implied value of waiting; then we iterate value functions until convergence. Finally, given assignments at the converged values of waiting, we need to check if the secondary market clears. Thus, cursed by dimensionality, we are forced to compute a benchmark that is feasible to us, but infeasible to the planner.

⁵²The reader may be concerned that even the “sticker prices” for each BTO development might change in response to the government’s *own* policy changes. Suppose the government expanded supply in a particular development. Even if the effects of this policy “wash out” far in the future, it may be that contemporaneous resale prices fall. If the government had a responsive pricing rule (not disclosed in detail as of this writing), they might then lower the “sticker price” of said development in which they expanded supply. We argue, given the set of covariates available to us, that contemporaneous resale prices fail to explain the residual variation in the “sticker prices” of each development. We first regress the “sticker price” of each development on our covariates, obtain the residual from that regression, then regress this residual on contemporaneous resale prices and the number of apartments in the offered development; see Table 20. We fail to reject the null hypothesis that contemporaneous resale prices and development quantity do not explain the residual variation in “sticker prices.” Therefore, the government likely does not price according to information that we do not have.

1. Simulated wait times
2. Apartment vacancies
3. Prices on the secondary market

These summary statistics map directly into outcomes the Singapore government cares about, as elucidated in Subsection 3.2. The primary objective is to assign young households to apartments as soon as possible, subject to budget and incentive constraints. These households benefit by having a home in which to settle down and start a family; the government gains from decongesting the “queue” of active applicants. Moreover, vacant apartments should be minimized, as they are expensive for the government to hold and (re-)allocate. Finally, existing homeowners should not have their apartments collapse in value, jeopardizing home equity they could draw down for retirement.

Changes in these outcomes are displayed in Table 9. In the actual mechanism, we directly observe development vacancies and mean prices on the secondary market. First, the Singapore government allocates 88% of the apartments it offers at BTO through the mechanism, so it is mostly successful at avoiding vacancies. By way of comparison, as of 2018, half of the 200,000 partially complete Mehr Project apartments in Iran were “left without prospective buyers” ([Radio Farda 2018](#)). Second, prices on the secondary market over the sample period averaged S\$460,000, against S\$100,000 for the median household’s income from work in 2015. The (secondary market) apartment price to median income ratio is thus 4.6:1, very slightly exceeding the 4:1 “rule of thumb” measure of housing affordability preferred by the Singapore government. We note that our chosen measure is conservative in two ways: we consider the mean price of all secondary market transactions in Singapore, not just those in neighborhoods farther from the city center. Moreover, prices on the secondary market are higher than comparable apartments allocated at BTO. After considering these two mitigating facts, we find that public housing in Singapore was affordable in general between 2012 and 2015.

Third, the poor wait 1.5 years to be assigned to an apartment, against 10 months for the rich. After being assigned, each household has to wait approximately 3 years for their development to be built. Therefore, households can wait upwards of 4 years between starting their search and taking possession of their apartment. For a (distant) comparison, between 2010 and 2014, among the developments administered by the Cambridge Housing Authority in Massachusetts, 327 successful applicants waited between 1.6 to 3.8 years before being housed ([Waldinger 2021](#)). We note that these numbers are not directly comparable because the Singapore and Cambridge programs differ in scale and purpose. The Singapore mechanism targets households from the 5th to the 80th percentile of incomes, i.e. not the destitute. These households are more likely to be able to wait for their preferred development than the agents in Cambridge are.

Outcome	Baseline	Building 10% more	Changing rules	Combined
Vacancies	12%	16%	7%	10%
Wait times	Poor: 1.5 years	↑0.4%	↓8%	↓8%
	Rich: 10 months	↓3%	↓23%	↓23%
2° market prices	S\$460k	↓0.02%	↑12%	↑9%

Table 9: Table of key outcome comparisons between the actual mechanism and three alternate policies in the sample period of January 2012 and May 2015. The three alternative policies are: when 10% more apartments are built in each oversubscribed development during the sample period; when the mechanism is changed to a dynamic variant of Random Serial Dictatorship; and when the previous two policies are simultaneously implemented. Secondary market prices are means over the sample period. For the actual mechanism, vacancies and secondary market prices are computed from the data. Baseline wait times and all other quantities are computed from counterfactual simulations.

10.2.1 Building more apartments

Under the current mechanism, at the margin, adding supply is ineffective because demand substitution undoes the supply response. If the designer builds 10% more apartments in oversubscribed developments, vacancies rise from 12% to 16%. Wait times fall slightly for the rich, by about 3%. However, the poor do not wait less. These findings contrast with the case where developments are homogeneous: in that scenario, wait times would unambiguously fall. In our setting, when supply expands in competitive developments, agents may substitute from a “safe” development today to a “risky” development tomorrow, i.e. choosing to wait *longer* to gamble for a better apartment. Though substitution attenuates the effect of expanded supply on wait times, the rich still wait about 1.3 weeks less on average.

More notably, prices on the secondary market remain unchanged. This effect is unsurprising to us: a 10% expansion of supply in oversubscribed developments represents a 7.8% increase in the flow of apartments between January 2012 and May 2015. Since the flow of apartments is minuscule relative to the stock, prices on the secondary market do not change.

In summary, because of substitution within a period and across periods, the demand response almost completely undoes the effect of added supply.

10.2.2 Changing rules

Our proposed strategyproof mechanism successfully reduces vacancies and wait times, but at the cost of higher (short-term) congestion on the secondary market. Vacancies fall from 12% to 7%, and wait times decrease by 8% for the poor and 23% for the rich. Two economic forces are at play. First, agents benefit from being allowed to list more than two developments (and/or exiting) in the same period. Since more agents are matched to developments within the mechanism, vacancies fall. Next, instead of failing at a development late in their search, an agent may prefer exiting early. Therefore, on average, agents wait less. However, since more agents exit, prices on

the secondary market must rise to incentivize owner-occupiers to sell their units. These prices rise by 12%, a substantial amount.

These findings demonstrate that rule changes are not free: spillovers on the secondary market benefit owner-occupiers at the expense of young households. Is there a way to mitigate the increase in prices on the secondary market?

10.2.3 Changing rules and adding apartments

In our final counterfactual, we adopt the aforementioned mechanism and also have the designer build 10% more apartments in oversubscribed developments. In this intervention, we find that adding supply partially alleviates the price increase in the secondary market. Relative to the true mechanism, vacancies fall from 12% to 10%. Wait times fall by similar magnitudes as in the scenario where only the rules were changed. The added supply relieves upward pressure on prices in the secondary market, leading them to rise by only 9% (as opposed to 12% when only DA was implemented).

Given the supply increase, young households still substitute away from undesirable developments to more popular ones. Thus, 10% of apartments remain vacant, as opposed to 7% when only the rules were changed. However, at the margin, young households benefit from the added capacity in desirable developments, so fewer of them exit to the secondary market.

Thus, our main takeaway from this section is that adding supply alone is not a panacea for congestion. Policymakers must pay attention to the rules through which this supply is allocated.

11 Conclusion

We study how public housing can be allocated more efficiently and equitably. In particular, we evaluate what happens when the rules are changed, when more apartments are built in overdemanded developments, and when the two interventions are combined. To this end, we combine tools from Urban Economics and Industrial Organization to estimate a dynamic choice model over housing lotteries.

In our setting, a key source of inefficiency is intertemporal risk: if an agent applies for a competitive development today and fails, she cannot go back in time and “settle for” a safe development in a previous period. To target this source of inefficiency, we consider a strategyproof mechanism eliminating intertemporal risk.

We also consider what happens when the government builds slightly more apartments in oversubscribed developments. We find that better rules complement building more apartments. Expanding supply alone fails to reduce wait times because of substitution within and across periods. However, under our proposed mechanism, wait times and vacancies fall, but at the cost of higher prices on the secondary market. In the new mechanism, building more apartments not only preserves the lower wait times, but also relieves some of the upward pricing pressure on the secondary market.

Our framework and insights on market design and supply control are applicable beyond public housing. Previous work investigates environments in which the designer cannot directly supply the good, like kidney donation ([Agarwal et al. 2021a](#)) and school choice ([Abdulkadiroğlu and Sönmez 2003](#)). We bridge a gap between the former settings and that of platform design on two-sided marketplaces (see e.g. [Dinerstein et al. 2018](#)). Typically, platforms intermediate between customers and sellers, needing to keep prices low to attract customers while sharing enough surplus with the sellers so that they do not exit ([Lee and Musolff 2023](#)). A similar dynamic is present in our setting: the government must conduct policy that balances housing access for young agents against preserving home equity for existing owner-occupiers. In Singapore, the effects of higher supply on the housing market depend on the rules under which the supply is allocated. Similarly, a platform could control the supply of goods on the marketplace it hosts (e.g., AmazonBasics). How does control over supply interact with the rules by which products and merchants are recommended?

Our approach comes with several caveats. In our model, we do not permit agents to learn from past play. In our setting, we believe this restriction is not first order, since households only apply for one apartment each period and are given ample information about current and future developments. Moreover, we abstract from state transitions in household financial status and family size, since we do not observe these variables at the individual level. Because most households are matched to apartments in less than 2 years, we believe these concerns do not detract from our mainline results. More can be done with better household-level data: this way, one can investigate differences in apartment choice probabilities when applicants expect a baby in the near future.

Finally, little is known about where the government should optimally locate public housing, given that local amenities respond to large changes in the housing stock. In future work, we intend to embed our allocation problem in a general equilibrium setting to answer these questions.

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12 Appendix

A Additional descriptive statistics

A.1 Additional correlation plots

Our main data set used in estimation has 195 rows and 36 columns. We scraped the HDB website for data on BTO application cycles from August 2010 to November 2015 and subsetted it to January 2012 to May 2015. From each news release on the HDB website, we obtained the town, size, quantity and price details of each BTO development. These details were merged with aggregate application data on the HDB website after each BTO cycle has concluded. Finally, we corroborated the HDB data with resale flat prices from <http://data.gov.sg>, as well as amenity data from <http://onemap.sg/>. Our amenity data take the form of, for instance, “distance in kilometers to nearest MRT (metro) station.”

In Figure 5, we correlate the main dependent variable in our analysis, *application rates*, with our main covariates. In this analysis, the key amenities are the distances to downtown, the nearest metro stop and the nearest Special Assistance Plan (SAP) school. As in the previous paragraph, the closer a development is to any of these amenities, the higher application rates are, all else equal. These amenities are correlated in the expected direction with the average price of an apartment within each development.

A.2 BTO apartments are oversubscribed

BTO apartments are typically oversubscribed by a factor of at least 2:1. Below, in Table 10, we display selected BTO application rates in the May 2015 cycle. Apartments in non-mature estates generally see lower oversubscription than in mature estates, owing to their being farther away from the city center and other amenities.

From our conversations with BTO applicants and government officials, we learned that when a household is offered an apartment within the mechanism, they almost always take it up. This observation arises because if an applicant forfeits her spot, she loses priority and becomes exceedingly unlikely to be matched in a future cycle. What few unmatched apartments exist are then offered to households applying to irregular clearinghouse cycles.⁵³ Motivated by these observations and to improve model tractability, we do not allow households to reject apartments they have been matched to, and assume that the PHA only shortlists applicants up to 100% the housing supply.⁵⁴

⁵³In Table 14 in the Appendix, we display application rates for one such clearinghouse cycle, the May 2018 Sale of Balance Flats exercise.

⁵⁴In practice, the PHA shortlists households up to three times the housing supply, resulting in almost all apartments in a development being matched to some household.

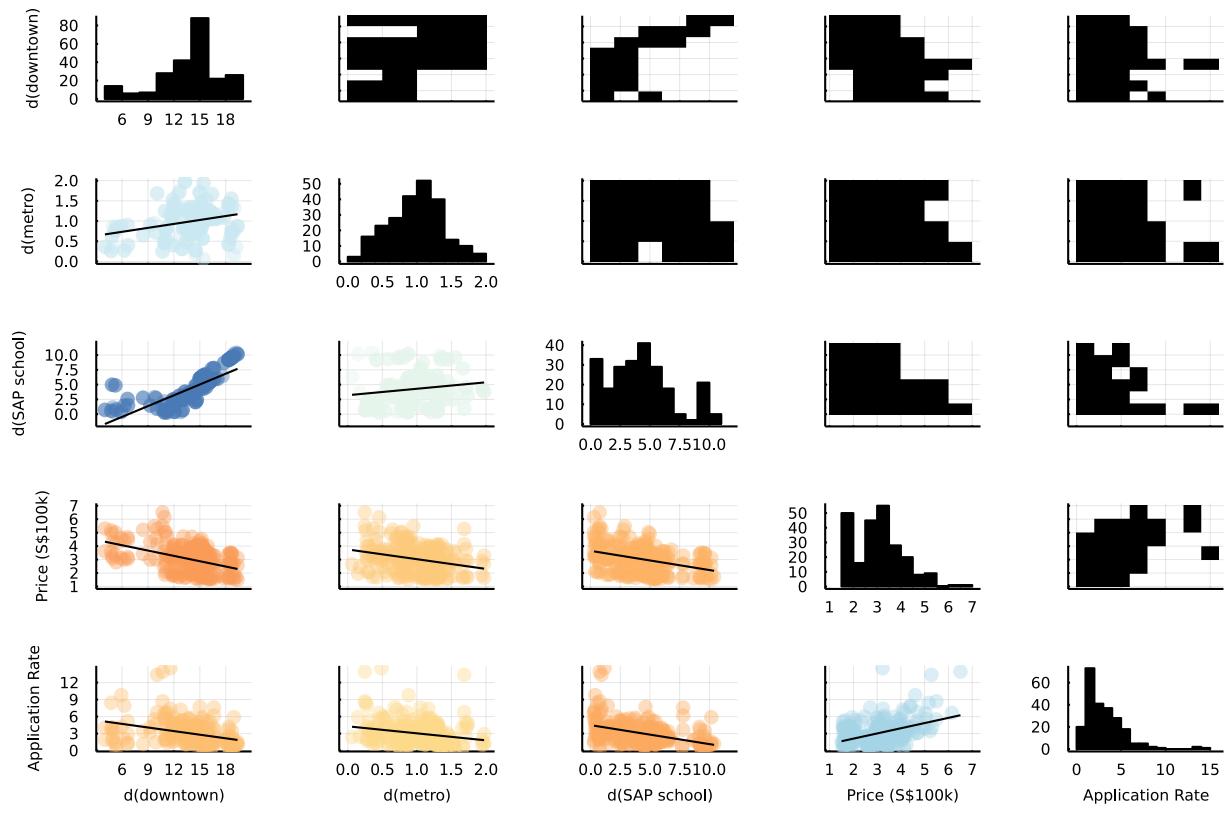


Figure 5: Correlation plot of selected variables against application rates (# applications / # quantity). Distances to downtown, the nearest metro stop and the nearest Special Assistance Plan (SAP) school are in kilometers. Redder (bluer) hues in each scatter plot indicate a stronger negative (resp. positive) correlation between the two plotted variables.

Neighborhood	Flat type	Units	Apps	Application rate
Non-mature				
Punggol	3-room	112	367	3.3
Punggol	4-room	519	1001	1.9
Punggol	5-room	225	658	2.9
Mature				
Clementi	4-room	229	1995	8.7
Clementi	5-room	156	2173	13.9

Table 10: Application rates (selected) for the May 2015 BTO cycle. These rates are computed by dividing the number of applications received by the number of units on offer.

A.3 Households are responsive to eligibility and explicit subsidies

Putative BTO applicants must make less than an income ceiling; this amount is S\$120,000 per year for the sample period used in our counterfactual analysis. For eligible households, explicit subsidies may be disbursed depending on their income and the apartment type they apply for. Generally, if a household is in a lower income bracket and/or is applying for an apartment in a “non-mature” estate, it will receive higher explicit subsidies.⁵⁵ See Table 18 in the Appendix for a comprehensive table of explicit subsidies.

A unique feature of our setting is that, conditional on a household’s income, we know exactly the effective prices they face when applying for a BTO apartment. To fix ideas, we focus on two income levels, with their subsidy levels listed in Table 11. Consider two households, one earning S\$36,000 a year (“poor”) and one earning S\$72,000 a year (“rich”). These values are calibrated to be the average incomes of the bottom 20% and top 80% of all applicants respectively. Under the subsidy regime active from August 2011 to August 2015, the poor household can obtain 2- and 3-room apartments for S\$20,000 off the sticker price, while the rich household does not receive any subsidy. However, after a policy change announced by the Prime Minister in August 2015, the poor household would have enjoyed a S\$60,000 subsidy on 2- to 4-room apartments in non-mature estates, with its subsidy on all other apartments unchanged. Meanwhile, the rich household now enjoys a S\$25,000 subsidy on the 2- to 4-room apartments in non-mature estates, with no subsidy on other apartments.

Income/Year	08/11-05/15		08/15-05/19	
	Full	Restr.	Full	Restr.
Poor (\$36,000)	\$20,000	\$20,000	\$60,000	\$20,000
Rich (\$72,000)	\$0	\$0	\$25,000	\$0

Table 11: Explicit subsidies for the two income levels in our example. Income and subsidies are denominated in nominal Singapore dollars. Full subsidies are applied to 2- and 3-room flats in non-mature estates in all time periods, as well as 4-room flats in non-mature estates starting November 2015. Restricted subsidies are applicable to all other apartments.

With the effective prices faced by every household, we can estimate how sensitive households are to changes in the explicit subsidy they face, all else equal. We will investigate this phenomenon in our counterfactuals; for now, we provide some evidence that households are responsive to subsidies. To do this, we adopt an event study framework. Before August 2015, no household was eligible for a full subsidy on 4-room apartments, by far the most popular apartment type. In August 2015, four policy changes were made:

1. 4-room apartments in non-mature estates became eligible for the full subsidy;
2. The income ceiling for households rose from S\$120,000 per year to S\$144,000 per year;

⁵⁵Current income ceiling data can be found on the [HDB website](#). Historical income ceiling data can be found in, for instance, the [July 2013 BTO application materials](#).

3. Households earning S\$60,000-S\$102,000 per annum became eligible for full subsidies;
4. Full subsidy rates rose.

We will compare application rates in non-mature estates across apartments of different sizes.⁵⁶ Our control group is the set of all 3-room apartments, which are always subsidized. We have two alternate comparison groups: the primary one is the set of all 4-room apartments, which were previously unsubsidized but are now subsidized. A secondary comparison group is the set of 5-room apartments, which are never subsidized but still may face higher application rates because of a higher income ceiling. Fix an apartment size j , location l and time t . Specify application rates as

$$\text{rate}_{jlt} = \xi_j + \xi_l + \beta \mathbb{1}\{t \in [T_0, T_1]\} + \gamma \mathbb{1}\{t \in [T_0, T_1]\} \times \xi_j + \epsilon_{jlt}, \quad (13)$$

i.e. fixed effects for apartment size and location, an indicator for the treatment time period, treatment interactions with apartment size, and an error term. The treatment time period spans August 2015 (T_0) and May 2019 (T_1). We are interested in the parameter γ . It tells us if application rates for 4- and 5-room flats differ from those of 3-room flats.

Our results can be found in Table 12. We find that 4- and 5-room flats saw higher application rates in the post-treatment period, relative to the untreated 3-room flats. However, there was no significant difference in application rates between 4-room and 5-room flats in the post-period, suggesting that the higher income ceiling and higher subsidies for 4-room apartments combined could have caused the higher application rates. Yet, in this procedure, we cannot definitively establish the aforementioned causal relationship. This is because application rates change in equilibrium. To recover causal parameters, we will write and estimate a model of the primary market for government housing, as in Section 7.

A.4 Implicit subsidies differ by apartment size and neighborhood

We define implicit subsidies given by the government as the difference between an apartment's sticker price at BTO and its five-year-ahead resale price. The government prices BTO flats below market rates "to ensure that new flats are affordable to buyers" (Wong 2017a). Though not much is known about how the government sets BTO prices, we believe it considers "the prices of comparable resale flats in the vicinity, as well as the specific attributes of the flats, such as storey height and design" (*ibid.*).

Such an implicit subsidy may be conducive to other policy objectives; for example, by making homes more affordable, the government is able to encourage family formation and fertility. However, such subsidies may not be allocatively efficient. Given that BTO apartments are over-subscribed, in a hypothetical decentralized market, there exist prices that exactly match demand with supply. Instead, in the BTO mechanism, the sticker prices set by HDB do not clear the mar-

⁵⁶See Figure 9 for the distribution of application rates to apartments in non-mature estates over time. We believe the parallel trends assumption holds.

Rate	Coef.	Std. Err.
Size		
4-room	-0.339	0.249
5-room	0.019	0.304
Treatment	-0.351	0.267
Size#Treatment		
4-room, Treated	0.966**	0.479
5-room, Treated	1.024*	0.538
Constant	2.544***	0.193
Town FE	Y	
N	227	

Table 12: Results for event study regression. Application rates to each development-apartment size pair are regressed against dummies for apartment sizes, post-August 2015 time periods through May 2019 (treatment) and interaction terms. Standard errors are clustered at the town, apartment size and time level.

ket for public housing, and provide an incentive for household arbitrage.⁵⁷ Figure 6 displays the implicit discount conferred upon households applying to each apartment type. We see that most apartment offerings are priced far below the five-year-ahead resale prices of similar apartments, with a mean of S\$88,000; yet there is a fair amount of dispersion, ranging from the BTO sticker price being S\$200,000 below to S\$50,000 *above* comparable resale prices.

To be clear, not every household who applies for a BTO flat solely values its resale potential; there is also “consumption value” in living in an apartment that is close to amenities. Yet the dispersion in implicit subsidies can be a powerful force spurring BTO applicants to prioritize apartments with higher resale value net of the sticker price.

A.5 Hedonic regressions

We display additional hedonic regressions exploring how distances to various amenities predict oversubscription rates. We specify our first regression as:

$$\text{rate}_{jlt} = x'_{jlt}\beta + \gamma d_{jlt}^{\text{SAP}} + \xi^{\text{mature}} \times \mathbb{1}\{l \in \text{mature}\} + \xi_j + \xi_t + \epsilon_{jlt}. \quad (14)$$

That is, we regress the number of BTO applications per apartment in each development (j, l, t), “rate”, on various amenity covariates and an indicator of whether the estate is mature. To control for persistent differences in application rates across apartments of different sizes and in different

⁵⁷One can view public housing apartments in our setting as being rationed by a combination of prices and wait times.

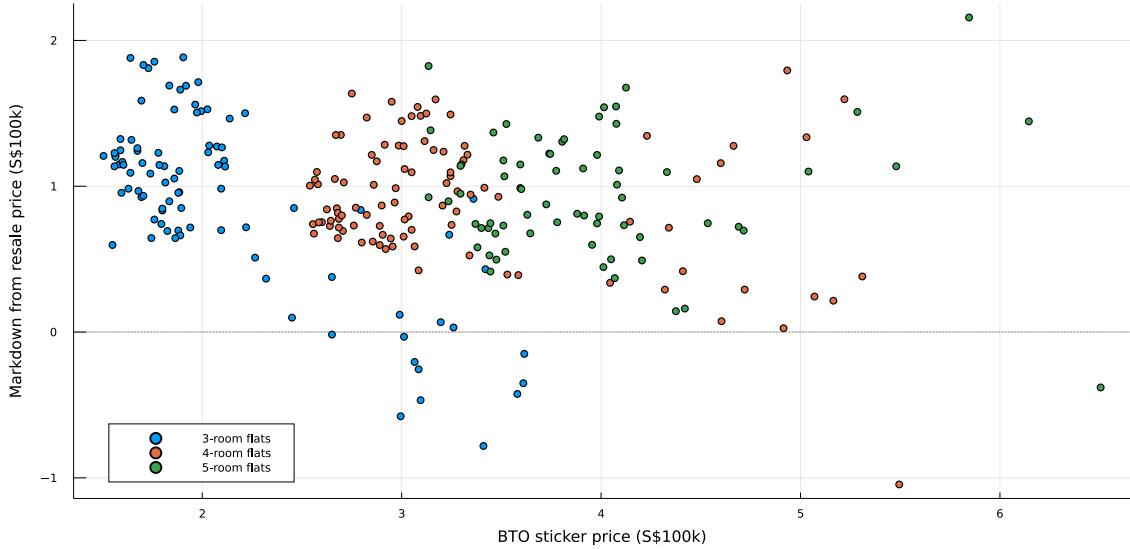


Figure 6: Implicit discount, by apartment type, of the BTO sticker price relative to the five-year-ahead resale price of similar apartments in the same neighborhood. Note that several of the smaller, cheaper apartments in mature estates actually see a negative markdown. Therefore, households opting for these units would pay for their apartment than they would have gotten had they liquidated their property immediately after living in it for 5 years.

BTO cycles, we include apartment size and time fixed effects.

Our results are in Specification (1) of Table 13. Our amenity covariates include the distance to the Marina Bay Financial Centre (a proxy for distance to downtown), to the nearest metro station, to the nearest hawker center, to the nearest supermarket, to the nearest non-Special Assistance Plan (SAP) school and to the nearest SAP school. We distinguish SAP from non-SAP schools to proxy for school quality: SAP schools specialize in bilingual education in English and Chinese and are academically competitive.⁵⁸ The regression coefficients we obtain are mostly as expected, though application rates are higher for housing estates farther from downtown. This could be because many households work in areas outside the city center.⁵⁹ Our other coefficients behave as expected. For example, an apartment 100 meters farther away from a metro stop is associated with a 0.104 lower application rate, all else equal.

A particularly noteworthy amenity is the proximity of an apartment to the nearest school. In Specification (1), we note that a 100m reduction in distance to a SAP school is associated with a 0.0292 higher application rate, all else equal. But we know more about the dependence between school distance and application rates: the distance to a school factors into admission priorities for first grade in Singapore.⁶⁰ Specifically, households living within 1 kilometer of a school have

⁵⁸By some measures, students in SAP schools receive additional funding relative to students in non-SAP schools; for instance, S\$300 per student is earmarked for “develop[ing] their proficiency and interest in Chinese language-related studies.” See, for example, [this statement](#) by then-Minister for Education Ong Ye Kung.

⁵⁹Many neighborhoods in Singapore are incompletely specialized between residences and workplaces. See [Lee and Tan \(2023\)](#) for more details.

⁶⁰The admission exercise for first graders (“Primary One Registration Exercise”) has a complex system of priorities

	(1) rate	(2) rate
mbfc	0.156** (0.029)	0.063 (0.097)
mrt	-1.057** (0.073)	-0.651** (0.220)
hawker	-0.803** (0.182)	-0.722** (0.196)
super	-1.406 (1.894)	-1.645* (0.851)
sch	-0.520 (0.311)	-0.820* (0.435)
sap	-0.292** (0.032)	
mature	1.278** (0.189)	0.773* (0.395)
sap <= 2		1.932** (0.141)
size FE	Y	Y
time FE	Y	Y
N	233	233
R2	0.399	0.353

Table 13: Regression results for hedonic (1) and boundary discontinuity (2) regressions for amenity access. We regress the number of BTO applications per apartment in each development, “rate”, on amenity covariates. Distances to the Marina Bay Financial Centre, the nearest metro stop, the nearest hawker center, the nearest supermarket, the nearest non-SAP school and the nearest SAP school are expressed in kilometers. Standard errors are estimated using the method of Spatial Correlation Principal Components ([Mueller and Watson 2021](#)). Stars indicate statistical significance at the 5% level.

the highest priority for admission to that school, followed by households living between 1 and 2 kilometers, and finally households living outside 2 kilometers. In our sample, very few BTO developments are located within 1 kilometer of a SAP school. However, several developments are located within 2 kilometers.

A first pass is to regress application rates on amenity covariates, as well as a dummy for whether the BTO development is within 2 kilometers of a SAP school. The results can be found in Specification (2) of Table 13. We find that apartments within 2 kilometers of a SAP school are about 1.9 times more oversubscribed than apartments outside 2 kilometers, all else equal.

To further clarify the dependence of apartment application rates on the distance to a SAP school, we collect BTO developments into 500-meter bins by distance, then regress application rates on dummies for each bin. The results are displayed in the left plot in Figure 7. We note that the mean application rate within the 2-kilometer boundary is about 2.5, which is about double that of the mean outside the boundary. To control for systematic differences between apartments within 2 kilometers vis-a-vis those outside the boundary, we control for the other amenity covariates and display the results in the right plot in Figure 7. Our results remain qualitatively unchanged. For robustness, we run falsification tests on average BTO price and distance to metro stop by distance to SAP elementary school, and find essentially no difference. These falsification plots can be found in Figure 10 in the Appendix.

We hesitate to interpret the results in Figure 7 as causal because of two possible confounders. The first is that apartments within 2 kilometers of a SAP school may have higher unobserved quality than apartments outside 2 kilometers. For example, SAP schools may be located adjacent to green or water features (by virtue of zoning requirements), so any “average treatment effect at 2 kilometers” would be confounded by the effect of proximity to natural features. The second is that BTO application rates are equilibrium objects. These objects depend on the choice sets of households in that particular BTO cycle, as well as *which* households choose to participate then. Therefore, a full structural model is required to disentangle substitution patterns between offered BTO apartments.

B Under new rules, do BTO applicants pay more for aftermarket apartments?

In our main analysis, we find that our proposed rules lower vacancies and wait times, but raise prices that young households pay for government apartments on the aftermarket. Could young households pay *less* for government apartments under the new rules? In two theoretical examples, we show that young households could pay less (or more) for aftermarket apartments.

If the secondary market were stationary, then, when more households are matched, prices should go down. However, in our sample period, aftermarket congestion was particularly severe in earlier periods. Under the new mechanism, households incur waiting costs by delaying their

which is beyond the scope of this paper. The first phase, for rising first-graders who have a sibling currently enrolled in the school, does not employ distance priorities. A minority of students enroll through this phase. Within each of the remaining phases, if there are more applicants than school places, distance priorities confer an absolute advantage in the subsequent lottery. See the [Singapore Ministry of Education website](#) for more details.

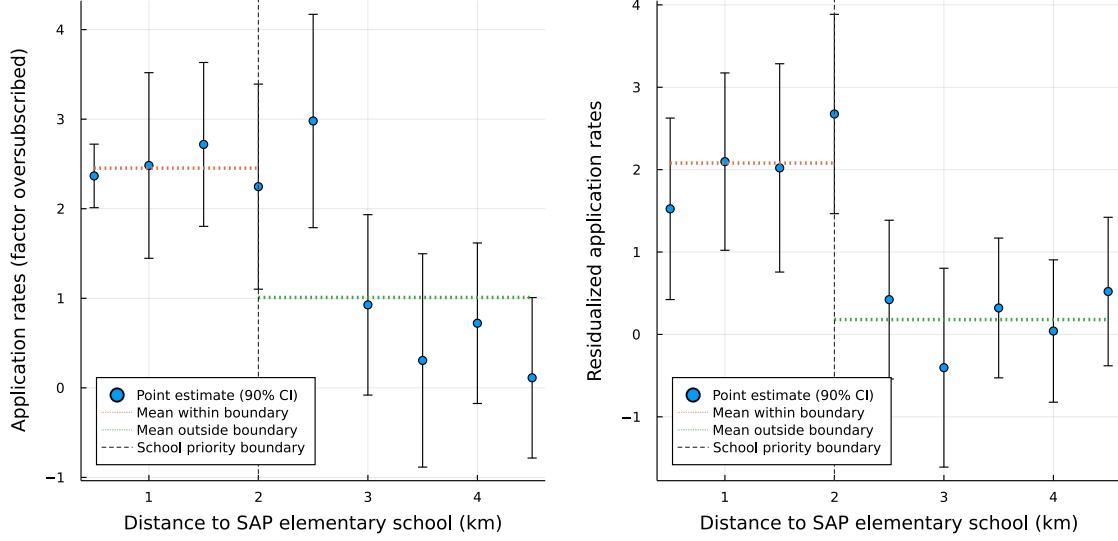


Figure 7: BTO application rates by distance to SAP elementary school. In our exercise, we examine the school priority boundary at the 2-kilometer mark.

applications. If they know they will not get their preferred apartments late in their search, they might prefer exiting early, even though they face higher prices in the short run.

B.1 Our proposed rules could lower average aftermarket prices

We first illustrate how, under our proposed mechanism, aftermarket prices may fall on average. As in the theoretical example section, There are two periods, $t \in \{1, 2\}$. In Period 1 (2), one house A (B) arrives. At the end of each period, vacant houses vanish. Three identical players $i \in \{1, 2, 3\}$ are born at the beginning of time and are perfectly patient. Every period, each active player i simultaneously takes one of three actions. She can apply for the available house; wait one period; or exit the market. If house j is oversubscribed, the winning agent is chosen via uniform random lottery. Agents who are matched to a house or exit the market stop making further decisions. If an agent waits or otherwise remains unmatched in Period 2, she exits the market.

Agents value house A at 0 utils and B at 10 utils. In any period, agents exiting the market receive a payoff of $-1 - P(n_E)$, where $P(n_E)$ is the aftermarket price. In this section, the aftermarket price only depends on the total number of households who exit. Assume agents face zero waiting costs, and set $P(x) = x$ for $x > 0$ and $P(x) = 1$ otherwise.

We seek a Subgame Perfect Nash Equilibrium in ex ante symmetric strategies. For the BTO mechanism, we conjecture that all households wait for and apply to house B. We solve for this equilibrium by backwards induction. Consider any subgame in which all three households are still unmatched at the start of the second period. Then, it is strictly dominant for them to apply

to house B over exiting. Their expected utility is thus

$$V_2(3) = \frac{1}{3} \times 10 + \frac{2}{3} \times (-1 - P(2)) = \frac{10}{3} - 2 = \frac{4}{3}.$$

In the first period, suppose all other agents passed on house A. Then the remaining agent should also pass on house A, because waiting gives higher expected utility than getting house A for sure:

$$v_1(w, -w) = \frac{4}{3} > 0 = v_1(a, -w).$$

Under this equilibrium, one agent is matched to house B and the other two agents remain unmatched. The price on the aftermarket is $P(2) = 2$.

Suppose we implemented our version of Random Serial Dictatorship. Since the mechanism is strategyproof, all agents truthfully express that they prefer house B to house A to remaining unmatched. The planner assigns one agent to house B, one to house A, and one to the aftermarket. The price on the aftermarket is then $P(1) = 1 < 2 = P(2)$. Therefore, under our proposed rules, aftermarket prices could fall.

B.2 Our proposed rules could raise average aftermarket prices

However, our proposed rules could also raise average aftermarket prices, especially if aftermarket congestion is severe in earlier periods.⁶¹ The key intuition is that, in lieu of paying waiting costs to “try for” developments late in their search, agents are willing to exit early, even if they pay higher prices on the aftermarket.

Suppose agents value house A at 1 utils and B at 3 utils. Their payoff from exiting is $1 - P_t$ utils, where P_t is the price they pay for an apartment on the aftermarket in period t . Between periods 1 and 2, agents incur a waiting cost of 1 util. In each period, housing supply is perfectly elastic, with prices $P_1 = 3/2$ utils and $P_2 = 1$ util respectively.

In the BTO equilibrium, we conjecture that agents apply for house A, then the remaining unmatched agents apply for house B. Consider any subgame in which two households remain unmatched at the start of period 2. Then, it is strictly dominant for them to apply to house B over exiting. Their expected utility is

$$V_2(2) = \frac{1}{2} \times 3 + \frac{1}{2} \times (1 - 1) = \frac{3}{2}.$$

In the first period, suppose all other agents apply to house A. Then it suffices to show that the

⁶¹In our sample period, aftermarket congestion in Singapore was much more severe in earlier years because of rapid population growth; furthermore, the government was slow to expand the supply of new apartments. Housing congestion and affordability played a role in the ruling party’s historically poor performance in the 2011 general election ([Chua 2017](#), p. 88). After 2011, the Housing and Development Board ramped up the supply of new BTO apartments. Combined with borrowing limits and transaction taxes on second homes, housing congestion was relieved substantially by the end of our sample period, contributing to the ruling party’s landslide victory in the 2015 general election ([ibid.](#), p. 94).

last agent has no profitable deviation by waiting or exiting in period 1:

$$v_1(a, -a) = \frac{1}{3} \times 1 + \frac{2}{3} \left(-1 + \frac{3}{2} \right) = \frac{2}{3} > \frac{1}{2} = v_1(w, -a) > 1 - P_1 = -\frac{1}{2} = v_1(e, -a).$$

Under this equilibrium, one agent is matched to house A, one to house B and the last exits in period 2. The average price paid by households on the aftermarket is $P_2 = 1$.

Under our version of Random Serial Dictatorship, all agents state that they prefer house B to A to exiting in period 1 to exiting in period 2. Under this mechanism, one agent is matched to house A, one to house B, and the last exits in period 1. The average price paid on the aftermarket is $P_1 = \frac{3}{2} > 1 = P_2$. Thus, under our proposed rules, it is possible for average aftermarket prices to rise.

In sum, whether aftermarket prices rise or fall depends on which economic forces dominate. If the aftermarket is stationary and the new mechanism successfully matches more applicants, then prices should fall. On the other hand, if agents are willing to pay to avoid incurring waiting costs, these agents may exit early, driving up aftermarket prices. Therefore, to evaluate the relative importance of these economic channels, we need to take our full model in Section 7 to the data.

C Motivating our specification of household preferences

In informal conversations with officials at the Housing and Development Board, we understood that BTO applicants tended to prioritize apartment size over development location, because “the difference in [apartment] sizes [is] rather substantial,” and

“And even for resale value, while in terms of [percentage] gains, smaller flat types might make sense, Singaporeans generally still lean to[wards] nominal profits.” —
Mr. XY⁶²

Despite the hefty subsidies given to successful BTO applicants, the official noted that only about 10% of BTO buyers eventually sold their apartments within 5 to 10 years of purchase, with about 5% of all HDB owners buying/selling an apartment in any given year.

We also spoke to participants in the BTO mechanism. They generally prioritized a development’s proximity to downtown, its distance to the nearest metro stop and its distance to the nearest mall.

D Estimation algorithm for demand

The computational procedure for demand proceeds as follows:

1. Set the GMM weight matrix W as the identity matrix.

⁶²Names have been changed to preserve confidentiality.

2. Guess a value of the parameters θ .
3. Given θ , compute structural residuals ξ and value functions V using a nested fixed point procedure:
 - (a) Given θ and a guess of ξ , iterate the value function V until convergence.
 - (b) Compute the path of market sizes M_t , type distributions $\mu_t(y, \tau)$ and model-implied market shares $s(\xi, V; \theta)$.
 - (c) If the model-implied shares $s(\xi, V; \theta)$ exactly equal the observed market shares \hat{s} , stop and return ξ . Else update $\xi \mapsto \xi'$ by taking a Newton step, then repeat steps (a) to (c) till convergence.
4. Form the GMM objective function specified in Problem 12.
5. If the GMM objective function is below a specified tolerance, stop and return the parameter estimate $\check{\theta}$. Else repeat steps 2 to 5 until the optimization routine has converged.
6. Given the estimated parameters, compute the optimal weight matrix $W(\check{\theta})$.
7. Repeat steps 1-5, replacing the identity matrix in Step 1 with the optimal weight matrix computed in step 6.

E Construction of Differentiation IVs

This section describes the construction of Differentiation IVs, previously sketched in Section 8.2.3. In the first stage, we regress the sticker price and forward resale price on cost shifters z_{at}^{cost} and exogenous amenities,

$$p_{at} = z_{at}^{\text{cost}'} \gamma^z + x'_{at} \gamma^x + \nu_{at}^P; \quad p_{at}^R = z_{at}^{\text{cost}'} \gamma^{Rz} + x'_{at} \gamma^{Rx} + \nu_{at}^R.$$

Then, we predict these prices, obtaining $\hat{p}_{at}, \hat{p}_{at}^R$. Finally, we construct quadratic IVs based on five variables; the two predicted prices and three distances: to downtown, to the nearest metro stop, and to the nearest SAP school. Our instruments are thus

$$z_{at}(x_t, p_t, p_t^R) = \left(\sum_{a \neq a'} (d_{at,a'}^{\hat{p}})^2, \sum_{a \neq a'} (d_{at,a'}^k)^2, \sum_{a \neq a'} d_{at,a'}^k \times d_{at,a'}^{\tilde{k}} \right); \quad \forall k \neq \tilde{k},$$

with the difference terms computed as

$$d_{at,a'}^k = x_{at}^k - x_{a't}^k.$$

F “Burn-in” procedure for initial conditions

We need to specify, at $t = 1$, the market size M_1 as well as the age and income distribution of active applicants μ_1 . These values are obtained implicitly by estimating the model twice:

1. (Assume initial conditions.) Assume that 16,000 households were active at the beginning of the sample period. As for the initial age and income distribution, we assume a 20:80 ratio between poor and rich households across all ages; then, we assume that the number of households of ages $\tau = 2, 3, \dots, 10$ decays at an exponential rate ρ . This exponential rate ρ is chosen such that

$$\sum_{y \in \{L, H\}} \sum_{\tau=1}^{\bar{\tau}} \exp(-\rho(\tau - 1)) \mu_1(y, 1) = 1.$$

2. Using the estimation procedure described in Subsection 8.2.2, obtain the parameter estimates $\hat{\theta}_0$ and recovered unobserved development qualities $\hat{\xi}_0$. Let the empirical distribution of unobserved development qualities be \hat{F}_{ξ} .
3. (Select a sequence of periods for “burn in.”) Given the development characteristics in periods $0, -1, -2, \dots, -4$ before the start of the sample, find a sequence of periods $t^b, t^b + 1, \dots, t^b + 4$ in sample with development characteristics most similar to that of periods $-4, -3, \dots, 0$.
 - (a) For each candidate 5-period sequence, compute the means and variances of observable development characteristics.
 - (b) Compute the mean squared distance between each candidate 5-period sequence and that of the “pre-period.”
 - (c) Select the sequence of BTO cycles that has the lowest mean squared distance.
4. Append the candidate sequence to the beginning of the sample. For each development j in the candidate sequence in pre-period t , draw an associated unobserved development quality $\tilde{\xi}_{jt} \sim \hat{F}_{\xi}$.
5. Repeat steps 1-2 with the augmented sample, holding the pre-period unobserved development qualities $\tilde{\xi}_{jt}$ fixed.

We augment the data because we see the development characteristics before our sample period, but we do not see the number of applicants with the correct priority level, i.e. “first-timers.”

G Counterfactuals: Computational details

G.1 Rule changes: Computation

Our rule changes shut down intertemporal risk for BTO applicants. Given a guess of prices on the secondary market, each applicant submits a rank-ordered list over developments offered over all periods in which she is active, as well as exiting in each period. Then, apartments in developments are assigned to applicants via Random Serial Dictatorship (RSD). Finally, the algorithm searches over paths of secondary market prices that clear the market for existing apartments. Since the problem is non-differentiable, we use the Nelder-Mead algorithm to search for secondary market prices.

The computational procedure proceeds as follows:

1. Simulate $I \times K$ sets of household idiosyncratic shocks to the attractiveness of each development (a, t) , waiting and exiting. For each simulation $k = 1, 2, \dots, K$, let the first $1, 2, \dots, I/5$ agents be poor and the remainder be rich. Also simulate K sets of priorities for each agent.
2. Guess a path of prices on the secondary market \vec{p}_t^S . Compute the quantity of secondary market apartments supplied in each period, $Q_t^S(\vec{p}_t^S)$.
3. In each simulation, for each agent (i, y, τ_0) , compute the utility of each development and exiting; as well as the flow utility of waiting one period in periods $\tau_0, \tau_0 + 1, \dots, \tau_0 + \bar{\tau} - 1$.
4. Given the computed utilities, for each agent, form preference lists over each development and exiting.
5. Given the preference lists and drawn priorities, run RSD to obtain the realized allocation of applicants to developments and exiting.
6. In each simulation k , given the realized number of exiters and secondary market supply, compute the excess supply of apartments on the secondary market.
7. If, in each period, the average excess supply of apartments on the secondary market across simulations is zero, stop and return the realized secondary market prices \vec{p}_t^S . Else update \vec{p}_t^S and repeat steps 1-7 till convergence.

G.2 Building more: Computation

Suppose the government built a different number of apartments. Households would then react to the policy changes, resulting in different implied success rates of applying to each apartment type. At the margin, some of these households may elect to exit the mechanism, driving up the prices of apartments currently on the resale market. To credibly evaluate these counterfactual policies, we will have to compute the equilibrium consistent with household reoptimization. Conditional on parameters, counterfactual subsidies, as well as apartment quantities, computing an equilibrium amounts to searching for a fixed point in apartment success probabilities q and mean secondary market prices \bar{p}^S .

From an algorithmic standpoint, finding a fixed point is difficult, as it is a high-dimensional non-convex root-finding problem. Computation proceeds as follows:

1. Guess success probabilities $q^{(0)}$ and secondary market prices $p^{S(0)}$. Denote by $\omega^{(0)} = (q^{(0)}, p^{S(0)})$ the putative fixed point.
2. At the hypothesized secondary market prices, compute secondary apartment supply $Q_t^S(p^{S(0)})$ for all t .

3. Given $\omega^{(0)}$, iterate each agent's value functions till convergence, obtaining choice-specific values $v(\cdot; \omega^{(0)}, \cdot)$ and conditional choice probabilities $s(\cdot; \omega^{(0)}, \cdot)$.
4. Given the new choice-specific values and probabilities, forward simulate the model from the initial market size and type distribution, obtaining a path of hypothesized market sizes $M(\omega^{(0)})$ and type distributions $\mu(\omega^{(0)})$.
5. Given the CVFs, CCPs, market sizes and type distributions, compute the demand for each development $D_t(a; \omega^{(0)})$ and exiting $Q_t^D(\omega^{(0)})$.
6. Obtain the implied odds of success at each development $\hat{q}(\omega^{(0)})$ and excess demand $Q_t^D(\omega^{(0)}) - Q_t^S(p^{S(0)})$.
7. If
 - (a) the implied odds of success are sufficiently close to the hypothesized ones, i.e. $\|\hat{q}(\omega^{(0)}) - q^{(0)}\| < \epsilon$ for a pre-specified tolerance ϵ ; and
 - (b) excess demand is sufficiently close to zero, i.e. $\|Q_t^D(\omega^{(0)}) - Q_t^S(p^{S(0)})\| < \epsilon$,

then return the putative fixed point $\omega^{(0)}$. Else take a Newton step; obtain a new guess $\omega^{(1)}$; and repeat steps 2 to 7 till convergence.

Here we discuss equilibrium existence and uniqueness. We observe that success probabilities q lie in $[0, 1]^{|\mathcal{A}|}$, a compact and convex set. Moreover, mean secondary market prices \bar{p}^S can be constrained to lie in $[0, \bar{p}^{S,\max}]^T$, also a compact, convex set. Furthermore, the mapping from ω to implied success probabilities and excess demand is a continuous function, by a standard large-market assumption and interpolation procedure. By Brouwer's Fixed Point Theorem (1911), this mapping has a fixed point ω^* .

However, there may be multiple fixed points consistent with model primitives.⁶³ Therefore, we select the equilibrium arising from starting our optimizer at the observed success probabilities and secondary market prices ω^{obs} .⁶⁴ In our robustness checks, when we start the optimizer at random feasible points, we obtain similar results for our counterfactual quantities of interest below.

H Channels driving our results

H.1 Under our current mechanism, could expanding supply ever “work?”

We find that, under the current BTO rules, expanding supply fails to substantially reduce wait times. We ascribe this failure to substitution: instead of “settling” for an apartment today,

⁶³We give a trivial example of multiplicities here. Suppose there are two apartments A and B , each giving utility zero, and the continuation value is also zero. If there are 3 households, application success probabilities $(0.5, 1)$ and $(1, 0.5)$ are two fixed points consistent with optimal choices.

⁶⁴To improve convergence, we use a derivative-based Interior Point Optimizer (Ipopt, Wächter and Biegler 2006) with the ma97 linear solver (Hsl 2021).

marginal agents apply for a competitive development tomorrow.

To “reverse” our results, we need to eliminate this substitution effect. Focus on a stationary environment with ex ante identical developments, only one income type and no exit. Agents have perfect foresight and discount the future by factor $\delta = 0.96$. Each period, 1 development is offered, with associated utility $u(a) = 0$. Suppose houses are always short, so success probabilities are $q_t(a) = 0.8$ for all t . Then the agent’s choice-specific value functions over applying and waiting are

$$v_{it}(a) = 0.8 \times u(a) + 0.2 \times \delta V + \epsilon_{it}(a); \quad v_{it}(w) = \delta V + \epsilon_{it}(w).$$

Assume that the shocks $\epsilon_{it}(\cdot)$ are distributed iid Type 1 Extreme-Valued with location $-\gamma^E \approx -0.577$. Then, the agent’s (stationary) inclusive value satisfies the recursive relation

$$V = \ln [\exp(0.2\delta V) + \exp(\delta V)],$$

or $V \approx 2.7844$. For all t , the market share of the development is then

$$s_t(a) = \frac{\exp(0.2\delta V)}{\exp(0.2\delta V) + \exp(\delta V)} \approx 0.1084.$$

Suppose that tomorrow, i.e. in time $t+1$, an unanticipated (MIT) supply expansion occurs, so $q'_{t+1}(a) = 1$. However, supply remains the same in all other periods: $q'_\tau(a) = 0.8$ for all $\tau \neq t+1$. Contrary to our findings, we claim that more people apply to today’s development: $s'_t(a) > s_t(a)$. To see this result, we compute the new choice-specific value functions tomorrow:

$$v'_{it+1}(a) = 1 \times u(a) + 0 \times \delta V + \epsilon'_{it+1}(a) = \epsilon'_{it+1}(a); \quad v'_{it+1}(w) = \delta V + \epsilon'_{it+1}(w).$$

Abusing notation, tomorrow’s inclusive value can be computed as

$$V' = \ln[1 + \exp(\delta V)] \approx 2.7398,$$

so the market share of today’s development becomes

$$s'_t(a) = \frac{\exp(0.2\delta V')}{\exp(0.2\delta V') + \exp(\delta V')} \approx 0.1087 > 0.1084 = s_t(a).$$

Thus, if developments do not vary much in quality over time, we “reverse” our supply expansion result.

I Auxiliary tables and figures

Neighborhood	Flat type	Units	Apps	Application rate
Non-mature				
Punggol	3-room (Income ceiling \$6,000)	25	195	7.8
	3-room (Income ceiling \$12,000)	32	70	2.2
	4-room	238	618	2.6
	5-room / 3Gen / Executive	106	354	3.3
Sembawang	3-room (Income ceiling \$6,000)	39	210	5.4
	4-room	49	383	7.8
	5-room / Executive	23	169	7.3

Table 14: (Selected) clearinghouse application rates for the May 2018 Sale of Balance Flats cycle. These rates are computed by dividing the number of applications received by the number of units on offer.

As of...	Ceiling (3-room and up)
08/2011	\$120,000
08/2015	\$144,000
09/2019	\$168,000

Table 15: Household income ceilings over time in nominal Singapore dollars per year. Households are typically married couples applying to live in an apartment together. Their combined income must be lower than the specified amount to apply for a BTO apartment.

# of Rooms	2	3	4	5
H/h income ceiling (p.a.)	\$84,000	\$168,000*	\$168,000	\$168,000

Table 16: Household income ceilings by apartment size in nominal Singapore dollars per year, as of September 2019. A few three-room apartments in non-mature estates may have an income ceiling of S\$84,000.

Town Type/ Number of Rooms	2	3	4	5
11/2011-05/2015				
Non-mature	\$60,000	\$50,000	\$25,000	\$10,000
Mature	NA	\$30,000	\$15,000	\$10,000
08/2015-05/2019				
Non-mature	\$80,000	\$75,000	\$60,000	\$5,000
Mature	\$40,000	\$20,000	\$5,000	\$0
09/2019-present				
Non-mature	\$80,000	\$75,000	\$60,000	\$45,000
Mature	\$80,000	\$60,000	\$45,000	\$30,000

Table 17: Maximal household explicit subsidies by apartment size and town type over time. Subsidies are denominated in nominal Singapore dollars per year. We did not specify a maximal subsidy for 2-room flats between November 2011 to August 2015 because the precursor to 2-room “flexi” flats starting November 2015 is not comparable with flats of the same size during the earlier time period.

	08/11-05/15		08/15-05/19		09/19-
Income (Mth)	Full	Restr.	Full	Restr.	
≤ \$1.5k	\$60k	\$40k	\$80k	\$40k	\$80k
\$1.5k-\$2k	\$50k+	\$35k+	\$75k	\$35k	\$75k
\$2k-\$2.5k	\$30k+	\$30k+	\$70k	\$30k	\$70k
\$2.5k-\$3k	\$25k	\$25k	\$65k	\$25k	\$65k
\$3k-\$3.5k	\$20k	\$20k	\$60k	\$20k	\$60k
\$3.5k-\$4k	\$15k	\$15k	\$55k	\$15k	\$55k
\$4k-\$4.5k	\$10k	\$10k	\$50k	\$10k	\$50k
\$4.5k-\$5k	\$5k	\$5k	\$45k	\$5k	\$45k
\$5k-\$5.5k	\$0	\$0	\$35k	\$0	\$40k
\$5.5k-\$6k	\$0	\$0	\$30k	\$0	\$35k
\$6k-\$6.5k	\$0	\$0	\$25k	\$0	\$30k
\$6.5k-\$7k	\$0	\$0	\$20k	\$0	\$25k
\$7k-\$7.5k	\$0	\$0	\$15k	\$0	\$20k
\$7.5k-\$8k	\$0	\$0	\$10k	\$0	\$15k
\$8k-\$8.5k	\$0	\$0	\$5k	\$0	\$10k
\$8.5k-\$9k	\$0	\$0	\$0	\$0	\$5k
\$9k-\$10k	\$0	\$0	\$0	\$0	\$0
\$10k-\$12k	ineligible	ineligible	\$0	\$0	\$0
\$12k-\$14k	ineligible	ineligible	ineligible	ineligible	\$0

Table 18: Explicit subsidies by monthly income, apartment size and town type over time. Subsidies are denominated in nominal Singapore dollars. Full subsidies are applied to 2- and 3-room flats in non-mature estates in all time periods, as well as 4-room flats in non-mature estates starting November 2015. Restricted subsidies are applicable to all other apartments. “Ineligible” means that households of that income level are not permitted to apply for any BTO apartment at all.

	(1) price	(2) price	(3) price
Standardized price of concreting sand	0.163** (0.069)	0.140** (0.070)	0.293** (0.132)
Interacted with apartment size?	N	Y	Y
Other controls?	N	N	Y
N	195	195	195
R2	0.025	0.525	0.880
F	5.533	55.761	146.084

Table 19: Table of first stage regressions of BTO price on the standardized price of concreting sand. The second specification includes interactions of the price of concreting sand with the number of rooms of each apartment in the BTO development. The third specification further adds, as controls, distances to downtown and the nearest metro stop, interacted with apartment size and the instrument. We interact said distances with the price of concreting sand because developments closer to downtown and to metro stops are likely located on smaller land parcels, necessitating less concreting sand to build each development.



BUILD-TO-ORDER

Choose your home from 3 new Build-To-Order (BTO) projects that offer a total of 3,095 units of 2-room Flexi, 3-, 4-, 5-room, and 5-en flats:

- Canberra Vista in Sembawang
- Kim Keat Ripples and Toa Payoh Ridge in Toa Payoh

Apply for your choice town and flat type by **17 February 2020, Monday, 11:59pm.**

[Apply Online Now](#)

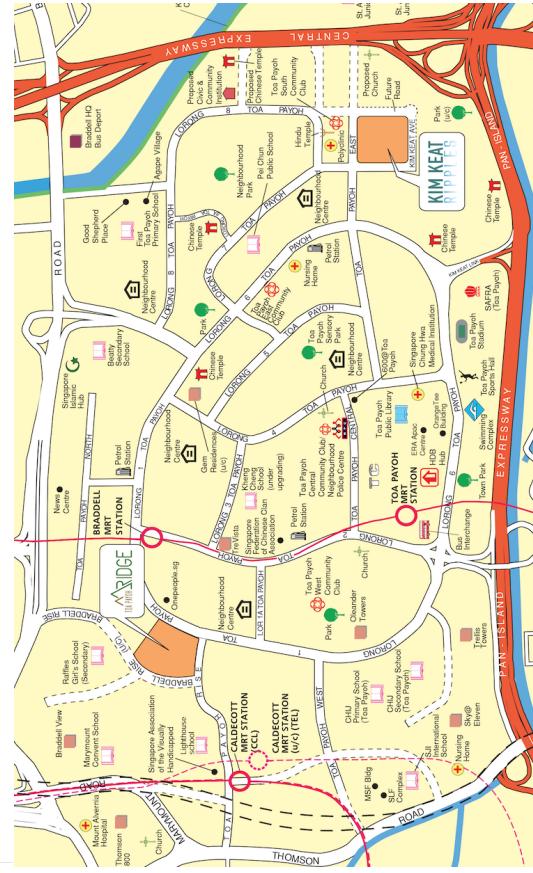
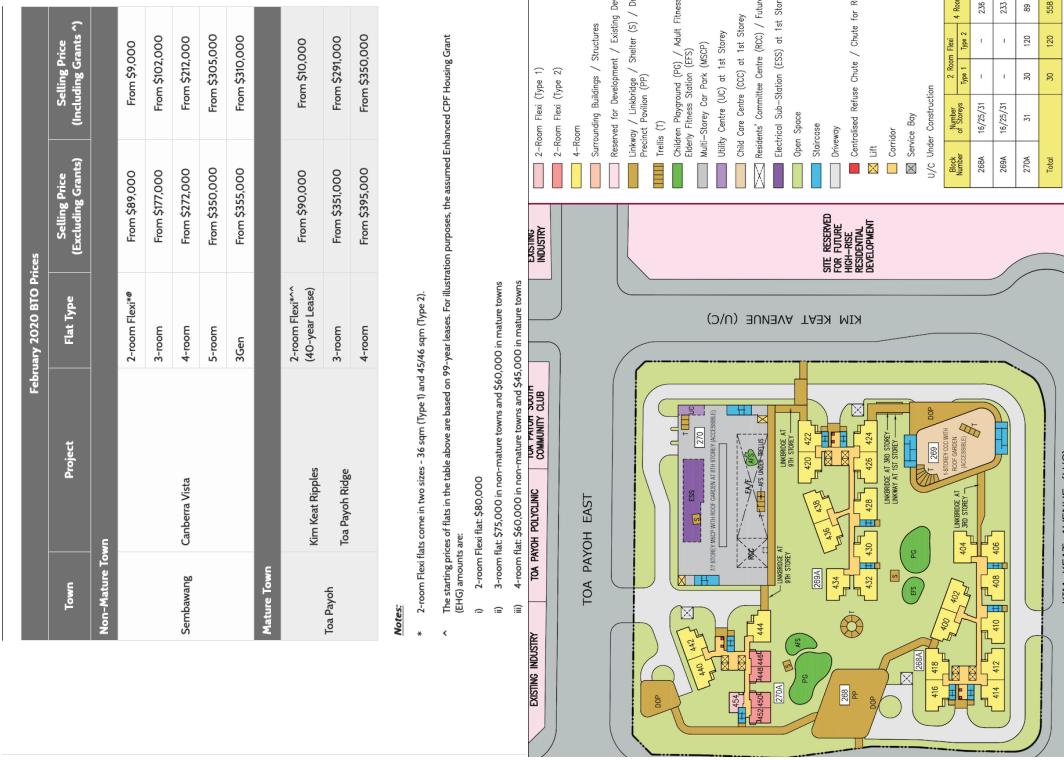


Figure 8: Information available to BTO applicants (clockwise from top left): Intro page for February 2020 BTO sales launch; Prices for that sales launch; Site plan for Kim Keat Ripples, a development in the February 2020 sales launch; Locality map for Kim Keat Ripples.

	(1) Residual Price
Contemporaneous resale price	0.0309 (0.0246)
Development Quantity	-1.72e-6 (4.08e-5)
(Intercept)	-0.137 (0.113)
N	193
R2	0.033

Table 20: Auxiliary “second-stage” regression results suggesting the government does not set prices based on contemporaneous prices of similar apartments, or the number of apartments offered in the same development. First, we regress each development’s “sticker prices” on our available covariates. After obtaining the residual from the first regression, we regress this residualized price on the number of apartments in that development, as well as contemporaneous prices of similar apartments sold in the same neighborhood and quarter. Standard errors are clustered at the neighborhood level.

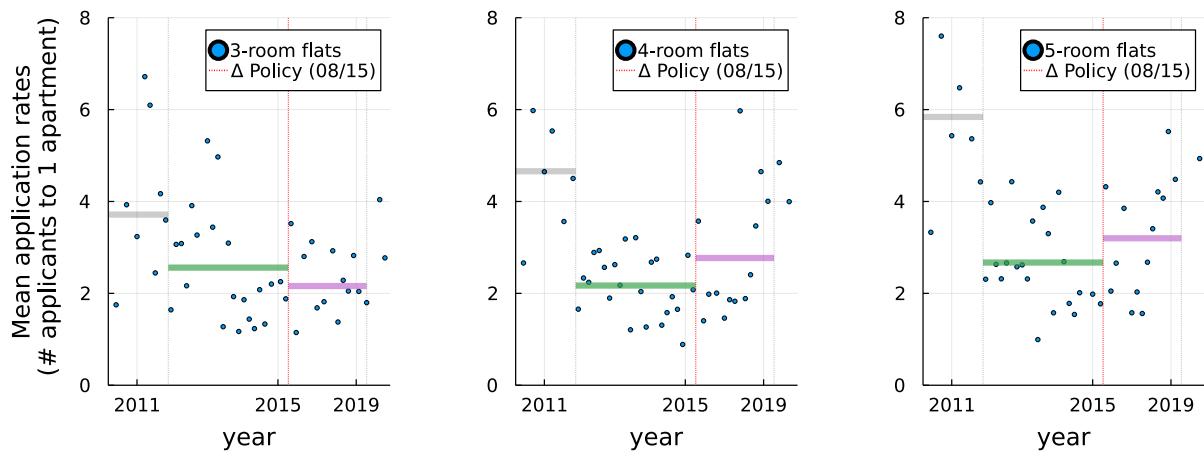


Figure 9: (Log) application rates by apartment size in non-mature towns. The application rate represents the number of households applying for each offered apartment. The three vertical red lines correspond to August 2011, August 2015 and September 2019, which are months of significant policy changes.

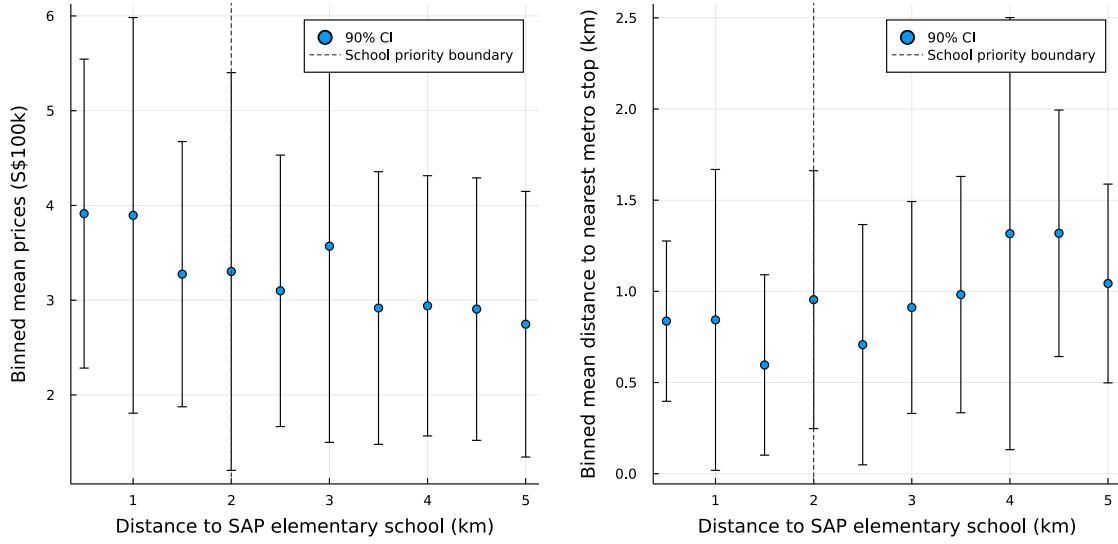


Figure 10: Prices and distance to metro stop seem evenly distributed across both sides of the 2-kilometer school priority boundary.

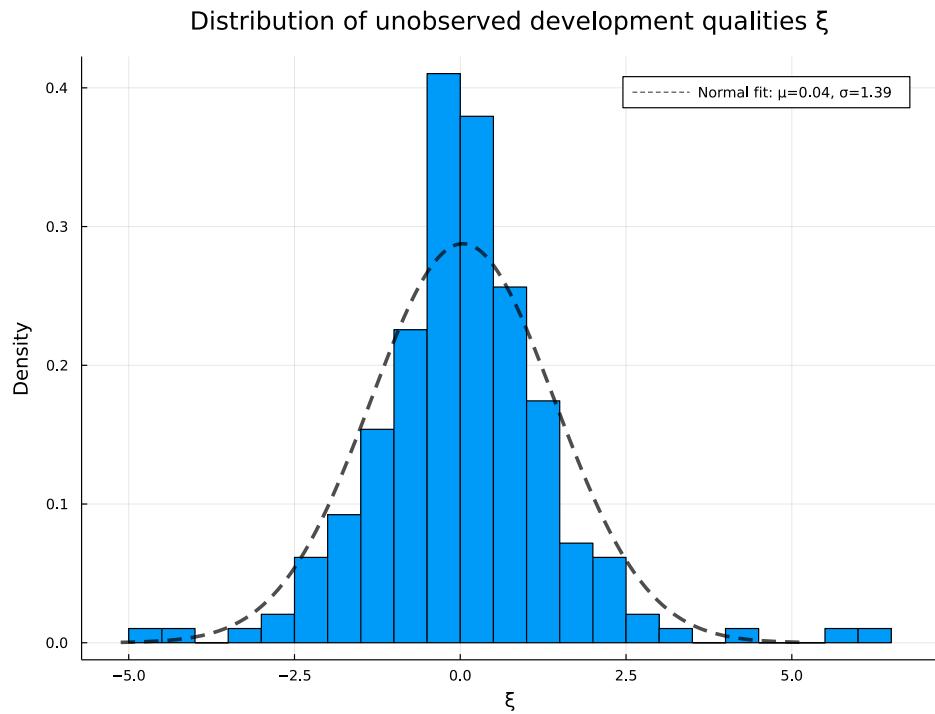


Figure 11: Histogram of the unobserved development qualities ξ recovered from our estimation procedure. Superimposed is the density of a normal distribution with the same mean and variance as the recovered qualities.

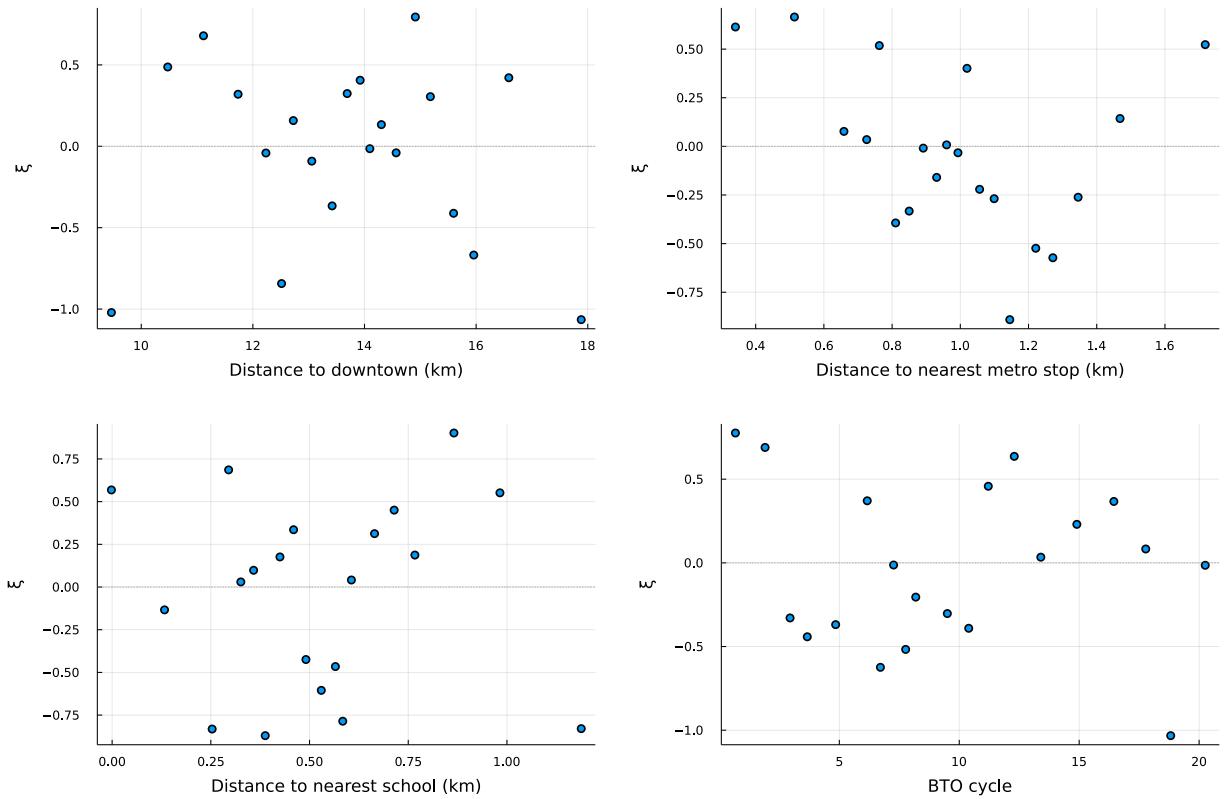


Figure 12: Binned scatter plots of targeted (top two) and untargeted (bottom two) moments. In each subplot, unobserved development quantities are residualized against the named covariate and the other covariates used in GMM estimation. The residualized ξ are neither more nor less dispersed as each named covariate increases. For each development, the targeted moments are its distance to downtown, proxied for by its distance to the Marina Bay Financial Centre; and its distance to the nearest metro stop. The untargeted moments are the development's distance to its nearest school, as well as in which BTO cycle it is offered. Distances are expressed in kilometers.