Estimating the Impact of the Ethnic Housing Quotas in Singapore

Maisy Wong [*,†]
University of Pennsylvania

October 5, 2012

Abstract

Desegregation is a key policy issue in many countries with diverse populations. These policies include quotas that affect many households but we know little about their impact due to data limitations. By hand-matching more than 500,000 names in the phonebook to ethnicities, I constructed a dataset of ethnic proportions at the apartment block level to study the ethnic housing quotas in Singapore. This policy was designed to encourage residential desegregation amongst the three major ethnic groups, the Chinese, Malays and the Indians. Using only apartment blocks close to the quota limits, I find moderate price effects and large negative effects on the proportion of units sold. I show that selection effects cannot fully account for these results. While quotas could have benefits by preventing extremely segregated outcomes that may not be desirable, my results show that costs can arise especially in markets with heterogeneous products and heterogeneous preferences.

[*]I wish to thank my advisers Professors Esther Duflo, Amy Finkelstein, Panle Jia and Bill Wheaton for guidance and support. I am also deeply indebted to Professors Peter Diamond, Michael Greenstone, two anonymous referees and the editor for their helpful comments. I have benefited from conversations with Professor Chua Beng Huat, Jessica Cohen, Greg Fischer, Raymond Guiteras, Kam Lee Ching, Trang Nguyen and Wong Liang Kit. I would like to thank the Singapore Housing Development Board for permission to use their data. This study would not have been possible without support from the MIT Shultz Fund. I am also grateful for financial support from the Zell-Lurie Real Estate Center. Lee Hye Jin and Chen Ying provided excellent research assistance. All remaining errors are my own.

[†]E-mail: maisy@wharton.upenn.edu; Address: 3620 Locust Walk, 1464 SHDH, Wharton Real Estate Department, University of Pennsylvania, Philadelphia PA 19104-6302.

1 Introduction

The seminal work by Thomas Schelling showed that private location decisions can affect the utility of neighbors by altering neighborhood compositions (Schelling, 1971).[1] Economists (including Schelling) argue that these externalities provide an economic justification for the coordinating role of public policies to avoid extremely segregated outcomes. Many of these policies take the form of quotas. In housing, examples include ethnic-based quotas in Starrett City in New York, religion-based quotas in a housing program in Andhra Pradesh in India and quotas for refugee settlements in Denmark and the Netherlands (Finder (1988), Banhardt (2009), Dutch Refugee Council (1999)). Beyond housing, there are also affirmative action quotas in Indian colleges (Bertrand et al., 2010) and American law schools (Rothstein and Yoon, 2008), in public service in India, Nigeria, Malaysia and South Africa (World Bank, 2005), gender quotas for corporate boards in Norway, France, Iceland and Spain (Corporate Women Directors International, 2012), hiring quotas in police departments in the United States (McCrary, 2007), political reservations in Indian village councils (Chattopadhyay and Duflo, 2004) and gender quotas in Spanish electoral lists (Casas-Arce and Saiz, 2011). In the United States, federal and state governments also impose race- or gender-based preferences through race- and gender-based targets in government procurement and federal contractor programs (Marion (2009), Leonard (1984)).

This paper studies the ethnic housing quota policy in Singapore. This policy was introduced in 1989 to encourage residential desegregation amongst the three major ethnic groups in Singapore – Chinese (77%), Malays (14%) and Indians (8%) (Singapore Department of Statistics, 2000). The policy is a set of upper limits on block level and neighborhood level ethnic proportions. Any transactions that forces the ethnic proportions of these blocks and neighborhoods farther above the upper limit is barred. For example, when Chinese quotas are binding, non-Chinese sellers cannot sell to Chinese buyers because this transaction increases the Chinese proportion farther above the Chinese quota limit.

These ethnic-based restrictions prevent some sellers of quota-constrained units from arbitraging price differences across ethnic groups. This price discrimination-like mechanism generates equilibrium price dispersion across buyers from different ethnic groups, making it possible, for example, to observe Chinese and non-Chinese buyers paying different prices for the same location, in equilibrium. This leads to price differences when comparing otherwise similar units just above and just below the quota limits. Depending on how easily prices can adjust, restrictions imposed by the quota policy could also reduce the proportion of units sold and increase the time a unit stays on the market.

[1] Recently, Pancs and Vriend (2007) showed that even if all individuals have a strict preference for perfect integration, externalities may lead to segregation.

To circumvent the problem that quota-constrained and quota-unconstrained locations are not comparable, I restrict my analysis to observations close to the quota limit. The strategy is to identify kinks in the outcome variable that coincide with kinks in the policy rule while controlling flexibly for the block-level ethnic proportions. While the setup is very similar to regression discontinuity design (Angrist and Lavy, 1999; Hahn et al., 2001), it does not fit within a standard regression discontinuity design (RDD) framework (Imbens and Lemieux, 2008; Lee and Lemieux, 2010) because the running variable of interest (ethnic proportions) is endogenous.[2] Therefore, the identification strategy is more similar in spirit to the regression kink resign in Card et al. (2009)'s study on the impact of previous earnings (an endogenous running variable) on unemployment insurance benefits.

There are relatively few studies on the impact of desegregation policies due to two challenges that I am able to circumvent.[3] First, many desegregation policies impose strict limits. For example, the VAMBAY housing program in Andhra Pradesh in India limit public housing clusters to be 75% Hindus and 25% Muslims. This means that clusters with more than 75% Hindus are unlikely to exist. By contrast, when the quota policy was implemented in Singapore in 1989, the Housing Development Board (HDB) did not want to evict owners in apartment blocks that were quota-constrained and they also wanted to minimize the number of households that would be affected. Therefore, they allowed all transactions that involved buyers and sellers of the same ethnicity because these transactions did not make the locations more segregated. Consequently, it is possible to observe housing transactions that are above the upper limits of the quota. The fact that many units exist above and below the quota limit will be useful for identification.

The second challenge is related to the data requirements of the identification strategy. Quotas are a nice natural experiment because kinks in the policy rule at the quota limits offer hope of identifying the causal effect of the quota policy by comparing units that are slightly above the quota limit to units that are slightly below the quota limit. However, this empirical strategy necessitates data on the running variable used to determine the quota status and a large number of observations, slightly above and below the limits. For the ethnic quotas in Singapore, the running variable of interest would be the ethnic proportions at the apartment block level. Since many of these policies are highly contentious, it is often hard to find public data of the running variable or even public data of the quota limits. For example, McCrary (2007) estimates the impact of racial hiring quotas in municipal

[2] To implement RDD, I would need pre-policy data on ethnic proportions. Unfortunately, I was not able to obtain it.

[3] For example, there is a vast empirical literature on the causes and consequences of residential segregation (Bajari and Kahn, 2005; Bayer et al., 2004; Card et al., 2008; Cutler et al., 1999; Gabriel and Rosenthal, 1989; Hårsman and Quigley, 1995; Ihlanfeldt and Scafidi, 2002) but relatively fewer studies of the impact of residential desegregation policies (Banhardt, 2009; Boisjoly et al., 2006; Edin et al., 2003; Rosenbaum, 1995)

police departments in the United States using event study analysis because "information on quotas is much more poorly measured than whether a city was litigated, and the date the litigation began" (p349). Bertrand et al. (2010) administered a survey to study the effect of affirmative action quotas in an Indian engineering college but "the strenuous data requirements of the regression discontinuity design methods coupled with (their) limited sample size reduced (their) ability to provide conclusive evidence on the returns to attending engineering school for the marginal admit." (p28).

I circumvent this data issue by hand-matching more than 500,000 names to ethnicities using the Singapore Residential Phonebook. This allows me to calculate ethnic proportions for 8007 apartment blocks. I combined this data with outcomes for 35,744 housing transactions that I downloaded from the HDB website.

An important identification assumption is that individuals cannot "precisely sort" around the quota limits so that variation in the treatment status around the policy limit is "as good as randomized" (Lee and Lemieux, 2010). I show that the *ethnic-specific* restrictions of the quota policy incentivizes sellers of different ethnicities to bunch on opposite sides of the quota limits. If seller ethnicity is correlated with income and housing upgrades is a normal good, price effects found at the quota limit could be the difference between upgraded versus non-upgraded units, rather than the treatment effect of the quota. I follow the RKD and RDD literature and test for discontinuities in the density of the running variable (McCrary, 2008). The density of the Chinese and Indian proportions are not statistically significantly discontinuous around the Chinese and Indian quota limits but not so for the Malay quotas. However, the bunching pattern around the Malay quotas is not consistent with households trying to manipulate treatment assignment but seems to be due to frictions in the housing market. Furthermore, the bunching pattern seems to bias against the price effects I find below. I return to this in the results section.

I find that Chinese-constrained units are 5 to 8% more expensive while Malay- and Indian-constrained units are 3 to 4% cheaper. Constrained units are also harder to sell. The proportions of units sold are 0.7% to 1.3% lower for constrained units. These effects are between 16 to 29% of the mean proportion of units sold (4.5%). I show that the results above cannot be fully explained by selection.

In the paper, I develop a theoretical framework with discrete choices where housing is heterogeneous and so are preferences for housing. Even though there are many housing units, as long as there is a high enough dimension of heterogeneity, housing units would be sparse in the attribute space, making the housing market thin (Arnott, 1989). This could lead to a wedge between a household's willingness-to-pay for his most desired unit and his second most desired unit. In the limit, as the housing market thickens, this wedge tends to zero. My framework shows that the price patterns are most consistent with segregation preferences (eg. Chinese prefer to live in Chinese neighborhoods more than non-Chinese prefer to live in Chinese neighborhoods) and thin markets for Chinese buyers (housing attributes preferred by the Chinese are sparse, given the preference distribution of Chinese buyers).

These findings have policy implications beyond Singapore. While quotas could be desirable due to externalities, costs from ethnic- or gender-based quotas are apt to arise in settings with thin markets. This is especially likely if preferences are heterogeneous by ethnicity or gender. I show that costs can arise even in Singapore, where the policy was designed to affect a small share of the population because transactions between buyers and sellers of the same ethnicity were still permitted and no one was evicted. Yet, there is still a sizable impact on the proportion of units sold, translating to significant increases along the time-to-sell margin, and a moderate impact on prices. Wong (2012) uses preference estimates from a structural neighborhood choice model to simulate the first best spatial allocation of ethnic groups and finds that a third of the neighborhoods are close to the first best allocation. The benefits estimated in the neighborhood choice model would have to be weighed against the costs estimated in this paper.

2 Background

Singapore is a multi-ethnic country with a population of 4.5 million (Singapore Department of Statistics, 2006). The three major ethnic groups are the Chinese (77%), the Malays (14%) and the Indians (8%). The Chinese have the highest median monthly income (S$2335), followed by the Indians (S$2167) and the Malays (S$1790). Although the median Malay household is poorest, the income distribution of the Indians have a longer left tail (more Indians are very poor). Also, the ownership rate in public housing is the lowest amongst the Indians.

Public housing is the most popular choice of housing in Singapore with 82% of the resident population living in public housing (Housing Development Board, 2006). The units are built and managed by the Housing Development Board (HDB). Public housing was first built in Singapore in 1960 to solve the young nation's housing crisis (Parliamentary Debates, 1989).

There are three ways Singapore residents can live in an HDB unit. They may apply through the primary allocation system for new HDB units,[4] they may purchase existing

[4]All eligible Singapore citizens can apply to buy new HDB units in the primary market. To be eligible, the applicant must be married, aged 21 and above and have gross income below a ceiling determined by HDB for that year. The primary market comprises mostly new HDB units that are built-to-order in new HDB estates. Most applicants are first time buyers because applicants must not have interest in any other property within 30 months of the application. Applicants can submit a request for one of the 8 HDB types of units and also a preference for one of the 3 HDB zones (North, North East and West). A computer ballot

HDB units in the resale market or they may rent. The rental market is negligible (98% percent of the HDB units are owner-occupied) because rentals are regulated to ensure that public housing is used for primary residences only (Housing Development Board, 2006).[5] This paper focuses on the resale market only.

Public housing in Singapore is based on the concept of new towns: self-contained, large scale satellite housing developments that usually includes public housing units, a town center and a range of amenities. HDB dwellings are relatively uniform. To cater to the different needs of households, HDB designed and built 8 unit types. Type 1 is a studio, Type 2 is a 1-bedroom unit, Type 3 is a 2-bedroom unit. Types 4 to 6 all have 3 bedrooms, but the higher types have extra living and/or dining areas. The remainder 2 types are called HUDC and multi-generation units. These tend to be larger units but HDB built very few of them. The most popular units are type 3 to 6. Apart from the number of rooms, the layout and size in public housing units are relatively homogeneous.

To understand the ethnic quotas, it is important to understand the geography of housing markets in Singapore. The smallest spatial unit is an HDB *unit*. An HDB *block* is a multi-storeyed apartment block with an average of 74 households. HDB *neighborhoods* are clusters of HDB blocks. The average neighborhood in Singapore has 4000 households, 45 HDB blocks and an average land area of 1.5 square miles. Due to the high population density in Singapore, a neighborhood is comparable to a US Census block group by land area but it is comparable to a US Census tract by population size. HDB *towns* are clusters of HDB neighborhoods.

Figure 1 shows a map of an HDB community with HDB blocks and HDB neighborhoods. HDB *blocks* and *neighborhoods* are terms used by HDB to describe clusters of public housing units. Throughout the paper, blocks and neighborhoods refer to HDB blocks and HDB neighborhoods. Each number in the map corresponds to an HDB block. Notice that the block numbers range from 100 to 600. There are 4 HDB neighborhoods in the map. All blocks that range from 100 to 199 belong to neighborhood 1 and all blocks from 200 to 299 are in neighborhood 2 and neighborhoods 4 and 5 are defined similarly. HDB neighborhoods are clusters of HDB blocks that are spatially contained, and separated from other HDB neighborhoods and other private housing by main roads. All HDB blocks and neighborhoods include public housing units only. There are no private housing units in this map.

Ethnic Integration Policy

will determine the applicants' queue position to book a unit. Lottery winners are given 3 months to select a new unit. They will typically wait 2 to 3 years before the unit is completed in the new HDB estate. After 5 years, the owners are free to sell their units in the resale market.

[5] In my sample period, owners of public housing are only allowed to rent if they can prove that they need to be out of the country for an extended period.

In late 1988 and early 1989, the government began to sound alarms about the growing "concentrations of racial groups" and the "gravity of this problem". They were concerned about going back to "the pre-1965 period when conditions bred distrust and misunderstanding among the various races and when there were even racial riots". The Minister for National Development pointed out as an example that in the town of Bedok, "if present trends continue, the proportion of Malays will reach 30% by 1991, and will exceed 40% in 10 years' time". He was also concerned that "once a critical point is passed, racial groupings accelerate suddenly". In response to these trends, the government announced the Ethnic Integration Policy in a parliamentary debate on February 16, 1989 and the policy was implemented starting March 1, 1989 (Parliamentary Debates, 1989).

The policy is a set of quota limits at the block and neighborhood level. Table 1 lists the limits, in comparison to the 2000 national ethnic proportions. There are block level and neighborhood level limits. They chose the HDB neighborhood as the basic unit to apply the quota because "the neighborhood is a distinct entity with a well-defined physical boundary". Quota limits were set depending on the rate of formation of new households as well as recent trends in applications. At that time, applications for HDB units did not reflect the ethnic composition in Singapore. Chinese, Malays and Indians accounted for 74%, 19% and 7% respectively. The neighborhood limits allow some flexibility relative to these proportions. The Chinese neighborhood limit was set at 84% (10% more than the share of Chinese applications), and the Malay and Indian neighborhood limits were 3% above these proportions (22% and 10% respectively). Block quotas were 3% above each neighborhood limit to allow some blocks to be more segregated relative to the neighborhood limit. It was important to the government to have specific limits that would be applied to "all the ethnic groups in all areas". They reasoned that giving a range would mean that "the limit will vary from place to place and this can give rise to a lot of suspicion and misunderstanding". Since then, the quota limits have been fixed over time and are also fixed for all areas (Parliamentary Debates, 1989).

The quotas are upper limits on ethnic proportions to prevent HDB communities that are already segregated from becoming more segregated. Once a community hits the upper limit, transactions that make the community more segregated will not be allowed.[6] However, transactions involving buyers and sellers from the same ethnicity will always be allowed because this does not increase the ethnic proportion. For example, Table 1 shows that the Chinese block level quota is set at 87%. Once the Chinese make up more than 87% of the HDB block population, Chinese buyers can no longer buy from non-Chinese sellers

[6]These restrictions are easily enforced because the identity cards of all Singaporeans report their ethnicity. Also, all resale transactions have to be approved by the HDB. One of the approval steps involves checking whether the transaction violates the ethnic housing quotas. An inter-ethnic married couple can choose to use either ethnicities of the spouses.

because this increases the proportion of Chinese in that block. Table 2 lists the types of transactions allowed or not allowed, for each ethnic quota.

The policy restrictions were designed to avoid extremely segregated outcomes without affecting too many households. For example, it was emphasized many times in the parliamentary debate that “no HDB owner, whether he is Chinese, Malay or Indian will be requested to move from his present flat”. Resale statistics at that time showed that most HDB owners who sold their flats sold to buyers of the same ethnic group. Since, the policy was designed to allow all transactions involving buyers and sellers of the same ethnicity, they estimated that fewer than 1700 owners would be potentially affected by the policy. The government also did not anticipate great price effects and reasoned that “it is a small price we must be prepared to pay in order to ensure that we do build a cohesive, better integrated society in Singapore” (Parliamentary Debates, 1989).

The policy appears to have reduced the Malay and Indian proportions in some places. For example, Lum and Tien (2003) report that the town of Bedok and Yishun had 59% and 24% Malays and Indians in 1988 but only 19% and 11% respectively by 1998. The third town they looked at, Redhill, started with 87% Chinese before the policy and still had 84% Chinese by 1998. There have been calls to relax the restrictions of the quota, especially when the “volume of transactions is actually very low and therefore the ability to sell the flat to the right ethnic group would be more difficult”. There were also complaints that the policy “is posing a serious financial problem to some families” (Parliamentary Debates, 2003).

In spite of these complaints, the government has repeatedly insisted on maintaining the quota limits. In fact, the policy was even extended to non-Malaysian permanent residents. Beginning in March 2010, HDB began to enforce neighborhood and block quota limits (5% and 8% respectively) on the share of non-Malaysian permanent residents. Malaysian permanent residents are not subject to the quota due to their close cultural and historical similarities with Singaporeans (both countries are former British colonies and Singapore was part of Malaysia for a short period in the 1960s). Using quotas to regulate location choices of immigrants is also not unique to Singapore. In Europe, many settlement policies place limits on where newly arrived immigrants can settle, mostly in an effort to avoid the formation of enclaves. In Netherlands and Denmark, this is achieved by placing limits on the number of refugees each municipality is obliged to provide dwellings for (Dutch Refugee Council, 1999).

2.1 Price effects at the quota limits

In this section, I layout a framework to analyze price effects around the quota limits. I focus on describing effects for the Chinese quotas only. The effects for the Malay and

Indian quotas are similar.

There is a perfectly competitive market of HDB units. Supply of HDB units is fixed and normalized to one. Every owner of an HDB unit is a potential seller. Sellers have an outside option (not moving).

Housing has two features: First, it is heterogeneous. Each housing unit is a bundle of attributes including the number of rooms, paint color, location, amenities and price. Second, housing is indivisible so that households cannot purchase fractions of units and combine them to obtain their ideal unit.

Demand for housing can be derived from a standard discrete choice model where households have heterogeneous preferences for attributes of HDB units.[7] Buyers have preferences over attributes of HDB units and choose the unit that maximizes their utility. The outside option is not moving. There are two groups of households: Chinese and non-Chinese. Chinese prefer to live in Chinese communities where there are more Chinese neighbors and more amenities and attributes preferred by Chinese.[8] Non-Chinese prefer to live in non-Chinese communities.

Because housing units are heterogeneous and taste for housing is also heterogeneous, even though there are many housing units, as long as there is a high enough dimension of heterogeneity, housing units would be sparse in the attribute space, making the housing market thin (Arnott, 1989). A consequence of thin housing markets is the existence of a wedge in willingness-to-pay between a household's most preferred unit and the second most preferred unit. In the limit, as the housing market thickens, this wedge tends to zero. Multi-dimensional heterogeneity in product attributes and preferences is one instance of a market inefficiency (relative to a Walrasian benchmark with identical consumers, sellers and homogenous products). There are many other features such as search costs, moving costs and credit constraints that generate transaction costs or frictions in the housing market (see Quigley (2002) for a review of the types of transaction costs in housing markets).[9] A common feature of models with these frictions is that households could be content with

[7]There is a large literature on sorting in housing markets (eg. Tiebout (1956), Benabou (1993) and Epple and Sieg (1997)). Location choice models that use a discrete choice framework builds on McFadden (1973, 1978), Berry (1994) and Berry et al. (1995). For examples of discrete choice models in the urban economics literature, see Quigley (1985), Nechyba and Strauss (1998) and Bayer et al. (2007).

[8]Examples of ethnic-specific amenities include kindergartens that teach ethnic languages, places of worship, community centers that set aside space for cultural events and activities for different ethnic groups (eg. *Tai-chi* for Chinese, *sepak takraw* courts for Malays and cricket fields for Indians). In a qualitative study of ethnic relations, Singaporeans indicated a preference for "special ethnic community places", suggesting that ethnic based taste for amenities could be important (Lai, 1995).

[9]I chose a model with heterogeneous products and heterogeneous preferences instead of a model with other types of frictions because it seemed the most natural choice to study a housing market with households from different ethnic groups. An alternative would be a dynamic search model but my data is most appropriate for a static framework.

not consuming their desired housing bundle if the transaction cost for the household is larger than the income equivalent gain in utility from changing their housing bundle.

In equilibrium, demand equals supply and buyers and sellers have no incentive to deviate from their choices. All buyers are utility-maximizing, given their preferences and the set of housing units in the market. All sellers are profit-maximizing.

The impact of the quota policy on prices, by buyer and seller ethnicity

The ethnic-based restrictions of the policy limits arbitrage opportunities and thus allows prices to differ across ethnic groups in equilibrium. Without the quotas, profit-maximizing sellers will sell to top bidders. With the quotas, even if Chinese buyers are willing to pay more than non-Chinese buyers for units in a Chinese-constrained neighborhood, non-Chinese sellers cannot arbitrage the price differences between Chinese and non-Chinese buyers because non-Chinese sellers cannot sell to Chinese buyers. Therefore, equilibrium prices can differ by the ethnicity of the buyer. I refer to this as the price discrimination effect of the quota.

If sellers are profit-maximizing, then, conditional on buyer ethnicity, prices will not differ by seller ethnicity. That is, non-Chinese buyers will not pay a different price for units sold by Chinese versus units sold by non-Chinese. This is because there are no policy rules that prevent non-Chinese buyers from arbitraging the price differences across seller ethnicity (they can buy from Chinese and non-Chinese sellers).[10] For Chinese buyers, they can only buy from Chinese sellers, so, there is no price difference by seller ethnicity. Therefore, to study the impact of the quota on average prices, we only need to keep track of prices by buyer ethnicity (ie. the price paid by Chinese and non-Chinese buyers).

The impact of the quota policy on average prices

Given the theoretical framework above, the sign of the overall impact of the quota policy on average prices is inconclusive because there are two opposing effects. To investigate the overall effect on prices, let Δ^+ denote weakly higher prices for Chinese-constrained units relative to unconstrained units and let Δ^- denote weakly lower prices. There are four types of transactions:

- Type I: Non-Chinese sellers and Chinese buyers (not allowed for Chinese-constrained units)

[10]One example of an arbitrage limit is ethnic discrimination (non-Chinese buyers may not be able to buy at the same price from Chinese and non-Chinese sellers if Chinese sellers discriminate against non-Chinese buyers). In this case, sellers are not profit-maximizing by accepting the highest bid because sellers who have a taste for discrimination may be willing to accept a lower bid from Chinese buyers than non-Chinese buyers (Becker, 1971). However, Wong (2012) finds preference estimates that are inconsistent with ethnic discrimination.

- Type II: Non-Chinese sellers and non-Chinese buyers (Price effect: Δ^-)

  Non-Chinese sellers have to lower their prices to attract non-Chinese buyers who would not have moved to Chinese-constrained units absent the quota. This price discrimination mechanism exists because of two features: the assumption that preferences are heterogeneous by ethnic groups (so that there are price differences to be arbitraged away in the first place) and the ethnic-based restrictions of the quota that limit arbitrage opportunities for some sellers.

- Type III: Chinese sellers and non-Chinese buyers (Price effect: Δ^-)

  Non-Chinese buyers will not pay different prices to buy from Chinese versus non-Chinese sellers as discussed above.

- Type IV: Chinese sellers and Chinese buyers (Price effect: Δ^+)

  Chinese buyers can only buy from Chinese sellers. $\Delta = 0$ if Chinese buyers are able to buy similar unconstrained units with similar amenities and location. $\Delta > 0$ if market thinness creates a wedge between a Chinese buyer's most preferred unit (that happens to be constrained) and his second most preferred unit (that happens to be unconstrained). How large the wedge is will depend on the buyers' elasticity of substitution. In a discrete choice model, the elasticity of substitution between constrained and unconstrained units will depend on the attributes for both types of units and also the preferences of the Chinese buyer.[11] If markets are thick so that the stock of housing is rich enough in attribute space (given the heterogeneous preferences of households), then, there should be no premium. The extent of the wedge (Δ^+) will depend on the interaction between the Chinese buyer's preferences and the attributes in the housing market.

The overall effect on prices will depend on the shares of each type of transaction (s_t) and the magnitudes of the price differences: $\Delta P = s_{II}\Delta^- + s_{III}\Delta^- + s_{IV}\Delta^+$.

The magnitudes of Δ^+ and Δ^- depend on the elasticities of substitution and also the differences in preferences between Chinese and non-Chinese buyers. If Chinese and non-Chinese buyers equally prefer to live in Chinese communities, then, there will be no price

[11]For example, a common utility function used in location choice models is linear in attributes with an additive and separable idiosyncratic error term that is Type I extreme value (eg. $u_{ij} = \alpha_i(y_i - p_j) + x_j\beta_i + \varepsilon_{ij}$ where u_{ij} is individual i's utility for unit j and y_i is income, p_j is the price, x_j is a row vector of attributes for the unit, α_i and β_i are marginal utilities and ε_{ij} is the idiosyncratic taste shock). Given this functional form, the price elasticity of substitution between unit j and unit k, $\frac{\partial s_j}{\partial p_k}\frac{p_k}{s_j}$, would be $\frac{p_k}{s_j}\int \alpha_i s_{ij} s_{ik} dF$ where F is the population distribution function s_{ij} and s_{ik} are the probabilities that individual i chooses unit j and unit k (these probabilities depend on the attributes of the units).

difference to arbitrage away in the first place. In other words, there would be no price discrimination mechanism ($\Delta^- = 0$).

Since all owners are potential sellers, bounds for the shares can be inferred using the quota limits and the ethnic proportions. Around the Chinese block quota limit (87%), we know that s_{II} is at most 13% (Chinese-constrained blocks have a maximum of 13% of non-Chinese sellers). Since Chinese are willing-to-pay more than non-Chinese buyers to live in Chinese communities, we can assume that most Chinese sellers will sell to Chinese buyers first ($s_{III} < s_{IV}$). Therefore, the overall effect on prices is likely to be heavily weighted towards Δ^+ than Δ^-, but the overall sign will still depend on the relative magnitudes of Δ^+ and Δ^-. A similar argument for Malay and Indian quotas suggest that the overall effects are heavily weighted towards Δ^-. This is because the Malay and Indian block quota limits are only 25% and 13% (so, s_{II} is likely to be high). These predictions are consistent with what I find below.

There are a few caveats to the framework above. First, it assumes prices are free to adjust such that the impact of the quota is fully captured by comparing prices of constrained and unconstrained units. If prices are not free to adjust (for example, due to loss aversion on the part of sellers (Genesove and Mayer, 2001)), then, the quota policy could also generate differences in other sale outcomes such as the proportion of units sold in a block and the time a unit stays on the market.

A more general model could allow supply to change but the assumption of fixed supply is appropriate given my sample period (less than two years). The supply of new units in the resale market is small during this time frame. New supply in the primary public housing market is likely to have less impact on prices in the resale market because households who participate in the primary market typically have to wait two to three years for a unit to be completed in the primary market. Also, income limits and other eligibility criteria suggest that many households who are eligible to buy in the resale market are not eligible to buy in the primary market (see Footnote 4 for more details). So, households who are potential buyers in the resale market are unlikely to be potential buyers in the primary market.

The framework above is static. A dynamic model could allow households to have expectations about whether the quota binds in the future. This type of forward-looking behavior would bias against finding discontinuities at the cutoff. For units right below the quota cutoff, if Chinese sellers knew that once the quota binds, there could be a premium for their units, the probability of capturing this premium should already be priced into units that are $\varepsilon\%$ below the quota. In this case, prices for Chinese-owned units should gradually increase as the percent of Chinese increases towards the cutoff. Equivalently, if non-Chinese buyers recognize that once the quota binds, there is a discrete downward jump in prices, this positive probability of the quota binding should be priced into units that are $\varepsilon\%$ below the quota. Hence, prices for non-Chinese-owned units should gradually decrease as the percent of Chinese increases towards 87%.

Finally, these price effects could lead to bunching/non-random sorting around the limits. Non-Chinese sellers will have an incentive to bunch slightly below the quota limit to avoid the negative price impact and Chinese sellers have weak incentive to bunch right above the quota limit. If sellers could "precisely sort" around the quota cutoff, then, a comparison of units right above and right below the cutoff could suffer from selection effects. Units sold below the cutoff would likely be owned by non-Chinese sellers (lower median income) and units sold above the cutoff would likely be owned by Chinese sellers (higher median income). If upgrades/renovations are a normal good and are not observed, then, this would essentially lead to a comparison of upgraded units above the cutoff and non-upgraded units below the cutoff. I test for bunching patterns below.

3 Data

Table 3 lists the summary statistics of the full dataset. The analysis only focuses on the public housing market which represents 82% of the citizens and permanent residents in Singapore. There are 8,007 blocks and 35,744 resale transactions. The Data Appendix includes more details on how the sample was created.

Ethnic proportions

The hardest data to obtain was the ethnic composition at the apartment block level because data on ethnic proportions at a fine geographic level are often not publicly available. To calculate ethnic proportions, I hand matched more than 500,000 names to ethnicities using the 2005 Singapore Residential Phonebook. It was published on April 1st 2005. Households can request for phone and address records to be unlisted at a charge of $20 per annum plus a one-time administrative fee of $20. One concern is that higher income groups are more likely to opt out. The sample size of the phonebook suggests that a majority of Singapore residents did not opt to be unlisted. The ethnic proportions calculated using the phonebook data are also similar to the national ethnic proportions, I did not detect a dramatically lower Chinese proportion (if higher income groups are more likely to be unlisted, then, I should find fewer Chinese names in the phonebook since the Chinese are the higher income group). Higher income groups are more likely to be in private housing rather than public housing and it is unlikely that this omitted household characteristic is different for constrained and unconstrained units. These suggest that any selection effects due to phone listing behavior is likely to be small and not different by ethnic groups.

There are 549,133 listings that correspond to HDB blocks in the Ethnic Integration Policy. I was able to match 548,024 names to ethnicities (a 99.8% match) using differences in the structure of Chinese, Malay and Indian names. For example, most Chinese names only have 2 or 3 words; Malay names are primarily Muslim names since 99% of Malays in Singapore are Muslims (Singapore Department of Statistics, 2000); Indian names are matched according to popular first and last names. Nevertheless, 1,109 names remain unmatched. Three listings were firms and 819 listings had names that only included initials or first names only and 287 listings had names with unidentifiable ethnicities (usually because I could not determine whether the names were Indian or Malay names). I dropped these unmatched names when constructing ethnic proportions (ie. the percent of Chinese in a block is calculated as the number of names matched as Chinese divided by the number of names in the block that were matched to Chinese, Malay or Indian). I also tried not dropping these 1,109 names and the results are similar.

The match between names and ethnicity is likely to be most accurate for Chinese names because of distinct last names.[12] On the other hand, Indian and Malay proportions may be more prone to measurement error because many Indian Muslims adopt Arabic names that are very similar to Malay names. Of the matched listings, 459,192 were matched using popular first and last names. Many Chinese names were matched this way. 84% of these names were identified as Chinese names, 13% were Malay names and 3% were Indian names. Another 88,832 names were matched individually. 50% of these names were identified as Chinese names, 17% as Malay names and 34% as Indian names. Overall, the ethnic proportions calculated using the phonebook were 78% Chinese, 14% Malay and 8% Indian, very close to the national proportions reported in the 2000 Census (77% Chinese, 14% Malay and 8% Indian).

Proportion of unit types

I purchased a non-public dataset from HDB that is the census of all HDB blocks in Singapore. The dataset includes the number of each of the eight unit types in each block, the street address and the HDB town. I use this dataset to create eight measures of the stock of HDB supply, measured as the proportion of units in an HDB block that is of each of the eight types.

Resale transactions

Every three months, HDB would upload resale transaction data for the past three months on their website. They publish data on the *type of unit sold*, the *square footage* of the apartment unit, the *year the HDB block was built*, which *floor range* the unit is in (eg. between floors one and five, floors six and ten), *price* and *month of sale*, street address and block number. I calculate the age of the HDB block as 2006 minus the year it was built. The final sample includes 35,744 transactions between April 2005 and August 2006.

Quota status

[12] Even Chinese Muslims would tend to keep their Chinese last names.

Each month, HDB publishes the quota status of all the HDB blocks in the Ethnic Integration Policy on their website. I downloaded these quota dummies every month from March 2005 to July 2006. In total, I have 133,378 block-months. The website only indicates whether an HDB block is constrained but does not specify whether it is because the block or neighborhood quota limit was constrained in that month. If all blocks in a neighborhood are constrained, I know the neighborhood limit is binding.[13] The quota data was missing for 117 block-months. See the Data Appendix for details on how I filled in the data for these 117 observations.

I matched the quota status of the previous month to each transaction so that the quota status of block *b* in November 2005 is matched to the transaction price for units in the same block in December 2005.[14]

Stayers

I do not have data on seller ethnicity, but I do collect data on the ethnicity of stayers in an HDB block by matching names and postal codes using the 2005 and 2006 phonebooks. Each phonebook includes six-digit postal codes that uniquely identify an HDB block. I am not able to identify addresses within an HDB block. I define stayers as households living in the same postal codes in 2005 and 2006. Since these are stayers, I know their ethnicity because I matched their listings in the 2005 phonebook to ethnicities. A majority of HDB households in 2005 are stayers. Therefore, I did not match names in the 2006 phonebook to ethnicity. This assumes that mobility between 2005 and 2006 did not change ethnic proportions much.

4 Empirical Framework

The challenge in identifying the treatment effect is omitted variables. For example, the price of constrained units could be higher than the price of unconstrained units (even if the treatment effect of the Chinese quota on prices is zero) because areas with more unobserved Chinese amenities tend to attract more Chinese, so, are more likely to be Chinese-constrained and more expensive.

The kink at the quota limit is key. The identification strategy relies on the step function of the quota status where units are unconstrained (the quota status is 0) below the quota limit on ethnic proportions and units are constrained (the quota status is 1) above the limit.

My empirical framework is similar in spirit to the regression kink design (RKD) in Card et al. (2009). The strategy is to identify kinks in the outcome variable that coincide

[13] Neighborhoods are identified using the first two digits and the fourth digit of the postal code obtained in the phonebook.

[14] I repeated the analysis with a 3-month lag, instead of a 1-month lag and the main results are similar.

with kinks in the policy rule while controlling flexibly for the assignment variable used to determine the policy rule (ethnic proportions). While the setup is very similar to regression discontinuity design (Angrist and Lavy, 1999; Hahn et al., 2001), it does not fit within a standard regression discontinuity design (RDD) framework (Imbens and Lemieux, 2008; Lee and Lemieux, 2010) because the running variable of interest (ethnic proportions) is endogenous. Therefore, the identification strategy is more similar to Card et al. (2009)'s study on the impact of previous earnings (an endogenous running variable) on unemployment insurance benefits. They argue that even though workers can control their earnings, lack of information on the precise location of the kink-point can rule out extreme forms of sorting. Below, I discuss whether households can precisely sort around the quota limits.

I estimate three sets of equations. I test for quota effects on three sets of outcomes: *lnprice*, the *type of unit sold* and the *proportion of units sold*. I restrict my analysis to observations within 10% of the Chinese, Malay and Indian block quota limits respectively. The key regressors in the first two equations are at the block-month level and the key regressor in the final equation is at the block level. I describe the equations for the Chinese quota. The empirical set up for the Malay and Indian quotas are similar.

The following two equations use the assignment dummy from the HDB website as the key independent variable. Equation (1) only controls for smooth functions of the running variable, while equation (2) controls for other observable characteristics:

$$y_{ibkt} = \alpha + \beta \; QC_{bk,t-1} + \sum_{l=1}^{4} \phi_l \left(percentC_{bk} - 0.87\right)^l + \varepsilon_{ibkt} \tag{1}$$

$$\begin{aligned} y_{ibkt} = \alpha + \beta \; QC_{bk,t-1} + \sum_{l=1}^{4} \phi_l \left(percentC_{bk} - 0.87\right)^l \\ + B_{bk} \; \delta + \tau_t + \omega_k + \varepsilon_{ibkt} \end{aligned} \tag{2}$$

where y_{ibkt} is the outcome variable for transaction i in block b, town k and month t; $QC_{bk,t-1}$ is a *dummy for whether the Chinese quota was binding in the previous month*, $(percentC_{bk} - 0.87)^l$ are l^{th} order *polynomials of the Chinese proportion*, centered around the block quota limit, B_{bk} includes observables for the HDB block, including the *age of the HDB block* and its squared, *proportion of units in a block that is of each of the seven HDB types* (type 1 is the omitted group); τ_t and ω_k are month and town fixed effects. The standard errors in (1) are clustered at the block level and standard errors in (2) are clustered at the town level.[15]

[15] I also tried estimating ethnic proportions separately for constrained and unconstrained blocks. The coefficient estimates are similar but not significant for some specifications when standard errors are clustered. I report the estimates using separate polynomials in the appendix.

The final equation is at the block level:

$$y_{bk} = \alpha + \beta \; percent \; QC_{bk} + \sum_{l=1}^{4} \phi_l percentC^l_{bk} + B_{bk} \; \delta + \omega_k + \varepsilon_{bk} \tag{3}$$

where *percent* QC_{bk} is the *proportion of months the Chinese quota is binding in the sample period*.

There are several limitations to the empirical framework that are mostly data driven. First, the ideal running variable would be pre-policy ethnic proportions at the apartment block level. Since the policy was announced and implemented within 3 weeks, this would have been an ideal natural experiment because households would not be able to manipulate treatment assignment by sorting. For various reasons, data on ethnic proportions are not publicly available at the local level and I was not able to obtain the 1989 phonebook.

Since I am using post-policy ethnic proportions that could be subject to sorting, I test for the presence of sorting by examining the densities of the running variables. I also calculate whether constrained blocks are geographically clustered using the dissimilarity index. This measure is frequently used in the housing literature to measure residential segregation.

The identification assumption is that all households are unable to precisely control treatment assignment around the threshold so that variation in the treatment assignment around the limit is as good as randomized. It is not a violation of the identification assumption if households can exert some control over the running variable as long as they do not precisely control on which side of the limit they land (Lee and Lemieux, 2010). It is hard for households to sort precisely around the quota limit because they do not know how close they are to the limit without knowing the ethnic proportions. Moreover, HDB only reports monthly indicator variables of whether an apartment block is constrained but does not publish the history of each block's treatment status. It is not straightforward for households to infer how close blocks are to the quota limit by identifying blocks that are frequently switching between the constrained and unconstrained status.

Absent the pre-policy data, the next best candidate would have been *monthly* administrative data on ethnic proportions that HDB uses to determine whether a block is quota-constrained or not. Using names in annual phonebooks to proxy for monthly ethnic proportions introduces two sources of measurement error. First, names may not match perfectly to ethnicities. If this measurement error is classical, this should bias against estimating any discontinuities. Even if names are perfect measures of ethnicities, annual phonebooks miss the monthly variation so that the actual quota status could be constrained for some months even though the annual ethnic proportion is below the quota limit. Another approach would be to use switchers (apartment blocks that switch from constrained to unconstrained across months or vice versa) but there are too few switchers during my sample period.

Finally, I have a limited set of observables compared to other studies of housing markets. While the number of controls is small compared to other studies of housing markets, besides location and unit type, the layout and size of HDB units are quite standard. I am able to explain up to 95% of the variation in prices by using just sale type dummies, block fixed effects and month-of-sale fixed effects.[16] I control for location using town and neighborhood fixed effects. HDB neighborhoods are comparable to census block groups by area.

5 Results

Figure 2 shows estimates of the densities of the running variables (McCrary, 2008). As shown in Figures 2a and 2c, the densities of block level Chinese and Indian proportions are not statistically significantly discontinuous at the quota limits. The log difference in heights are -0.048 (0.06 s.e.) and .009 (0.08 s.e.) respectively. Figure 2b shows that there is evidence of bunching right above the Malay quota limit. The log difference in height is 0.20 (0.08 s.e.). The bunching pattern around the Malay quota limit does not appear to be related to a manipulation of the treatment assignment. Furthermore, I will argue that this pattern of bunching cannot account for all the price effects found below. I return to this later.

Next, I test how evenly distributed quota-constrained blocks and neighborhoods are by calculating dissimilarity indices for block quotas and neighborhood quotas. This index is commonly used to measure residential segregation. It calculates the percent of households in an ethnic group who would have to change locations to produce an even distribution. Any location with an index between 30 to 60% is moderately segregated and locations with an index above 60% is very segregated (Cutler et al., 1999). Instead of counting black versus white households, I apply the same idea to count constrained versus unconstrained blocks or neighborhoods. If quotas are randomly assigned, we would expect constrained blocks and neighborhoods to be evenly distributed. A priori, it is unlikely that quota status is exogenous because ethnic proportions are correlated with unobserved ethnic-specific amenities (Chinese want to live near Chinese temples, for example). Nevertheless, it is useful to benchmark how clustered quota-constrained locations are.

Since there are quota limits at the block and neighborhood level, I calculate dissimilarity indices at the block and neighborhood level by using the monthly quota data from

[16] In Levitt and Syverson (2008), the most saturated regression specification explains 96% of the variation in house prices in Boston, using block fixed effects and a rich set of controls (including keywords in descriptions in the Multiple Listing Service). Using a similar dataset for the housing market in Wisconsin, Hendel et al. (2009) can explain up to 93% of the variation in house prices.

the HDB website. I first determine which blocks are constrained because of the block quota limit and which are binding because of the neighborhood quota limit.[17] To calculate the dissimilarity index for neighborhood quotas, I only keep blocks that are binding due to the neighborhood quota limit. Then, I collapse the block-month level quota data to the neighborhood-month level and I calculate the dissimilarity index for each month and average across months. That is, for each month *t,* I calculate:[18]

$$Dis_{Nt} = \frac{1}{2}\sum_{k}\left|\frac{\text{Number of constrained neighborhoods in town } k\text{, month } t}{\text{Number of constrained neighborhoods in Singapore in month } t} - \frac{\text{Number of unconstrained neighborhoods in town } k\text{, month } t}{\text{Number of unconstrained neighborhoods in Singapore in month } t}\right|$$

Likewise, to calculate the dissimilarity index for block quotas, I first keep block quota dummies only. Then, I calculate:

$$Dis_{Bt} = \frac{1}{2}\sum_{k}\left|\frac{\text{Number of constrained blocks in town } k\text{, month } t}{\text{Number of constrained blocks in Singapore in month } t} - \frac{\text{Number of unconstrained blocks in town } k\text{, month } t}{\text{Number of unconstrained blocks in Singapore in month } t}\right|$$

The average dissimilarity index for neighborhood quotas is 56% and the average dissimilarity index for blocks is 28% indicating that neighborhood quotas are moderately clustered but block quotas are relatively evenly distributed. It is possible that neighborhood quota status is correlated with unobserved amenities. I use neighborhood fixed effects to control for time invariant amenities at the neighborhood level. Some of the results are weaker but still statistically significant.

I test whether there is a jump in the probability that the quota binds at the block quota limit. To do this, I regress the *monthly quota status* from the HDB website on a dummy that is *1 if ethnic proportions are above the block quota limit* (measured using the phonebook data) while controlling for fourth order polynomials of ethnic proportions. Standard errors are clustered at the block level. Figure 3a summarizes the effect of being in a block with 87% or more Chinese on the probability that the Chinese quota binds in a month. Figures 3b and 3c measure the same effect for Malay and Indian block quotas.[19]

[17] The HDB website only publishes whether a block is quota-constrained but does not indicate whether it is constrained because the block or the neighborhood quota limit is binding. Once I merged this data with the phonebook data, I am able to use postal codes in the phonebook to determine which neighborhood each block belongs to (the first two digits and the fourth digit of the postal code determines the HDB neighborhood). If all the blocks in a neighborhood is constrained, then, I know it is because the neighborhood quota limit is binding.

[18] A typical dissimilarity index for black/white segregation in an MSA would calculate $\frac{1}{2}\sum_k \left|\frac{\text{Number of black households in census tract } k}{\text{Total number of black households in the MSA}} - \frac{\text{Number of white households in census tract } k}{\text{Total number of white households in the MSA}}\right|$.

[19] Figures 3b and 3c show a kink in the predicted probability around 50% above the Malay quota limit (25%) and the Indian quota limit (13%) because there are too few blocks with more than 75% Malays and more than 63% Indians, given that Malays and Indians are only 14% and 8% of the population.

There is a statistically significantly positive discontinuity in the probability that the quota binds, right at the policy thresholds associated with the Chinese, Malay and Indian quotas. The magnitudes of the jumps are 23%, 12% and 10% for the Chinese, Malay and Indian quotas (all significant at the 1% level). The probability that the quota binds is greater than 0 below the quota limits and less than 1 above the quota limits due to two reasons. First, there is time series variation because the quota data from the HDB website (vertical axis) is monthly and the phonebook data (horizontal axis) is annual. Conditional on the ethnic proportions from the phonebook data, whether a quota is binding or not can change from month to month. Secondly, there is measurement error in the matching of names to ethnicities, as discussed in the data section. The noise introduced by the measurement error would bias against finding discontinuities unless the measurement error is correlated with the quota status (non-classical measurement error), which seems unlikely.

Next, I use data from the HDB census to test whether the stock of HDB units is significantly different around the quota cutoffs (Table 4). Columns 1, 3 and 5 report results using all blocks that are within 10% of the Chinese, Malay and Indian quotas respectively. Columns 2, 4 and 6 report results using only blocks that were built before the policy started in 1989. The outcome variables are *proportion of type 3, proportion of type 4, proportion of type 5, proportion of type 6* units in each block.[20] The type of HDB unit is one of the most important attribute in public housing. The resale data published on HDB's website is organized by location and HDB unit type, presumably because many households search for comparable prices by unit type and location. A regression of *lnprice* on month-of-sale and neighborhood fixed effects explains 32% of the variation. Just adding dummies for the type of unit sold (from the resale data) increases the R-squared to 86%. Higher types are more expensive. The coefficient on these type dummies are monotonically increasing with types and almost linear if we plot the coefficient estimates of the type dummies on the vertical axis and the type of unit sold on the horizontal axis.

Chinese-constrained blocks have significantly more type 4 units, but significantly fewer type 6 units (column 1, Table 4). The proportion of type 3 and type 5 units are not significantly different. While these significant differences in observable attributes are a concern, it is comforting that the sign and magnitude of the coefficients are not monotonic in the type of the units. It does not appear that Chinese-constrained units tend to have systematically more high priced units even though the Chinese are the group with the highest median income. Differences between Malay-constrained and -unconstrained blocks are statistically and economically insignificant. Malay-constrained blocks have 2% more type 6 units (10% sig.), but the magnitude is small and this difference existed before the policy

[20]There are 8 types of units. I only used 4 types in the regression because there are too few type 1, type 2, type 7 and type 8 units in the resale market. The R-squared of a regression of *lnprice* on *proportion type* 3 to *proportion type* 6 is 0.65 and including the other types only increases the R-squared by 0.007.

(column 4). Indian-constrained blocks have fewer type 3 units and more type 4 and 6 units. These differences also persisted since before the quota policy was introduced (column 6).

However, it remains a concern that after controlling for smooth functions of observable characteristics, there could be unobservables that generate discontinuities in prices. In my analysis, I will report estimates with and without controlling for these observable characteristics. Most findings are robust to the inclusion of these controls. My preferred specification for price effects in Table 5 include town fixed effects, month fixed effects and town-by-month linear time trends and can explain 75% to 80% of the variation in prices (column 3). Finally, I follow Altonji et al. (2005) and show that selection on unobservables is unlikely to explain away the entire price effects I have estimated.

Table 5 reports statistically significant price effects around the Chinese, Malay and Indian quota limits. Column 1 only controls for polynomials of ethnic proportions. Column 2 adds controls on the *age of the block* and its squared, the *proportion of each of the seven types of units* (type 1 is the omitted group), town and month-of-sale fixed effects and column 3 adds town-by-month linear trends.

Chinese-constrained units are 5 to 8% more expensive. The size of these discontinuities represent 5 to 8 times the median monthly income of the Chinese (S$2,335).[21] Malay-constrained units are 3 to 4% cheaper and Indian-constrained units are 3% cheaper. These discontinuities are 3 to 5 times the median monthly income of the Malays (S$1,790) and 3 times the median monthly income of the Indians (S$2,167). Figure 4 illustrates these results on prices.

Following Altonji et al. (2005), I calculate how large selection on unobservables would need to be to explain away the entire price difference. To do this, I divide my preferred estimate with controls (column 3) by the difference between the estimate without controls (column 1) and the estimate with controls. The larger the magnitude of this ratio, the more unlikely it is that the effect estimated is driven by selection on unobservables. The magnitude of the ratio is large if the effect to be explained away is large (the numerator) or if controlling for more observables does not change the estimate much (the denominator is small). In their paper, Altonji et al. (2005) report that a ratio of 3.55 would make selection on unobservables "highly unlikely" and a ratio of 1.43 would make it seem "unlikely". The ratio for the Chinese quota is 1.61 [22] and the ratio for the Malay (Indian) quota is 2.15 (-6.12). Therefore, it seems unlikely that selection of unobservables can explain the entire price effect.

The price effects fall to 3%, -0.7% and -1% for Chinese, Malay and Indian quotas respectively when I control for neighborhood fixed effects instead of town fixed effects (column 4). HDB units can be constrained if they belong to HDB blocks that are above

[21] Calculated using the average price of units sold (S$234,000).

[22] Calculated using 0.050/(0.081-0.050).

the block quota limit or they belong to HDB neighborhoods that are above the neighborhood quota limit. Estimates with neighborhood fixed effects are smaller in magnitude because they are identified from comparing constrained and unconstrained blocks within a neighborhood, ignoring the effect of neighborhood quotas. Column 5 adds block fixed effects (there are no controls because all the controls are time-invariant attributes at the block level). Identification is from time series variation in the quota status of a block. The coefficient estimates are insignificant because there are too few blocks that switch quota status within my short sample period. The estimates using separate polynomials for constrained and unconstrained units are similar but there is less statistical power (see Appendix, Table A1).

Table 6 shows that the types of unit sold are higher-priced units for Chinese quotas, and lower-priced units for Malay quotas but the magnitude of the effects are small. I use an ordered probit specification where the dependant variable is an integer between one and eight, representing eight different types of HDB units.[23] I control for whether the quota is binding in the past month and fourth order polynomials of ethnic proportions. A higher number indicates a higher priced type. I find that Chinese-constrained units that are sold are of lower type even though the prices are higher. This is consistent with the finding of no bunching/smooth density of Chinese proportions. If non-Chinese sellers manipulated treatment assignment by bunching below the limit and Chinese sellers (higher income) bunched above the limit, this selection effect would likely lead to higher priced units being sold right above the limit but this is not what I find. This suggests that there exists frictions in the market (eg. because markets are thin or there is imperfect information about ethnic proportions relative to the quota limit) so that sellers are not able to precisely control the treatment status of their unit when it is sold. Conversely, Indian-constrained units that are sold are higher type (not significant) even though the prices of these units are lower. Malay-constrained units that are sold are lower type, consistent with the finding that the prices are also lower. The magnitudes of the coefficients are small. The marginal effects for the Chinese quotas translate to a 2.8% increase in probability for type 3 units and a 1.8% and 1.09% decrease in the probabilities for type 5 and type 6 units (all 10% significant). The magnitudes are also small for the Malays and Indians.

Table 7 reports the impact of the quota on the *proportion of units sold*. Panel A includes all HDB blocks that have appeared in the resale transactions website. Panel B includes all HDB blocks in the Ethnic Integration Policy website, including blocks that did not have a the resale transaction during my sample period (I set *proportion units sold* to 0 for these blocks). My preferred specification includes town fixed effects (there are no month fixed

[23] An alternative specification would control for type of unit sold in the analysis of price effects (Table 5). I did do this and the results on price effects are similar. I chose to report the effects on prices and type of unit sold separately because the latter is an endogenous choice and a potential outcome of the policy.

effects because this specification collapses the transactions level data used to estimate price effects to the block level) and includes blocks with no units sold during my sample period (Panel B, columns 2, 5 and 8).

The proportions of units sold are 0.7 to 1.3% lower for constrained units. These effects are between 16 to 29% of the mean proportion of units sold (4.5% if we include all blocks). The coefficient estimates translate to a 16 to 29% if we include all blocks. Another way is to translate these effects into durations. On average, 0.2% of units are sold in a month. A 0.8% effect translates to 4 months longer on the market for Chinese quotas. The duration is longer for Malay quotas (6.5 months) and similar for Indian quotas (4 months). These are relatively long durations. Ong and Koh (2000) report that the mean time on market is less than 2 months and the median is slightly longer than a month (42 days). The incidence of this effect is likely to fall on non-Chinese (non-Malay, non-Indian) sellers for the Chinese (Malay, Indian) quotas because Chinese (Malay, Indian) sellers can sell to all ethnic groups.

In summary, I find moderate price effects and relatively large effects on the proportion of units sold. Effects on type of units sold are small. Price effects could be moderate relative to the proportion of units sold due to loss aversion (prices are do not adjust freely) and the capitalization of expectations that biases against finding price effects.

Recall that I found evidence of slight bunching above the Malay quota limit (Figure 3b). One reason for this pattern of bunching is that Malays have very strong preferences for living in Malay enclaves perhaps because they tend to have larger families and want to live close to families. Since the policy had reduced the number of Malay enclaves tremendously, they have a lower propensity to leave Malay-constrained units. By matching names and postal codes in the 2005 and 2006 phonebook, I can identify stayers (see discussion in Section 3). Indeed, I do find that Malays are slightly more likely to stay in quota-constrained blocks.[24]

However, the bunching pattern with a slightly higher density of Malay proportions above the limit is unlikely to be due to Malays who are manipulating their treatment status. Moreover, it is also not consistent with the estimated price effects. Malay owners of constrained units face a trade-off of higher prices versus lower proportion of units sold. Given the magnitude of the estimates in Tables 5 and 7, it seems more likely that the latter effect would dominate so that Malays who are manipulating their treatment status would have more incentive to bunch *below* the quota limit. Even if they bunched above the quota cutoff because of the prospect of higher prices, this would then bias against the *negative*

[24] I looked at two outcomes: The number of stayers who are Malay divided by the number of households in a block and the number of stayers who are Malay divided by the number of stayers in a block. The estimates are 0.4% for the first outcome (relative to all households) and 3.4% for the second outcome (relative to all stayers). Both estimates are significant at the 1% level.

price effects that I estimate in Table 5. Therefore, bunching is unlikely to explain the price effects in Table 5 and appears to be inconsistent with households who are manipulating their treatment status.

Discussion of results

How should we interpret the effects estimated above? There are three primary channels which could lead to price differences for constrained and unconstrained units. First, constrained units are harder to sell (Table 7). This perception would likely lead to *negative* price effects for all three quotas. Second, there could be segregation preferences by ethnic groups in that Chinese prefer to live in Chinese locations (with more Chinese neighbors or near amenities preferred by Chinese) more than non-Chinese want to live in Chinese locations. Likewise for Malays and Indians. This pattern of preference heterogeneity, together with the arbitrage limits and price discrimination mechanism of the quota policy would lead to price dispersion for constrained units and *negative* impacts on average prices (this corresponds to type II transactions discussed in Section 2.1). Third, market thinness could lead to *higher* prices paid for quota-constrained units (this corresponds to type IV transactions in Section 2.1).

Overall, the pattern of positive price effects for Chinese quotas and negative price effects for Malay and Indian quotas is most consistent with segregation preferences and thin markets for Chinese buyers in that attributes preferred by the Chinese are sparse, given the preference distribution of Chinese buyers. But, there is less evidence of market thinness for Malay and Indian buyers. The first channel is likely to be weak. Otherwise, average prices would be lower for all three quotas. Moreover, Figures 4a to 4c support the second channel. They show that price dispersion is indeed larger for constrained units, indicating the price discrimination mechanism is in effect.[25] If segregation preferences were not strong, then, there would be no price difference across ethnic groups to arbitrage away in the first place and the ethnic-based restrictions of the quota policy would have no price discrimination effect. If this channel did not exist, we would not observe more price dispersion and lower average prices (for Malay and Indian quotas).[26]

Together, the results illustrate how costs can arise when constraints such as quotas are imposed. These results echo some of the findings in the literature. Bertrand et al. (2010) finds that caste-based affirmative action quotas in India reduce the number of females entering engineering colleges. Marion (2009) finds that removal of affirmative-action type restrictions for highway construction contracts in California led to a 5.6% decline in the

[25]I did test whether the variance in price is higher but there was not enough statistical power in the data.

[26]Alternatively, one could explain the positive effect on prices for Chinese quotas and the negative effects for Malay and Indian quotas using the negative impact of the first channel (constrained units are harder to sell) and the positive impact of the third channel (market thinness) for Chinese quotas. But, this would be inconsistent with the price dispersion in the figures.

price for state-funded contracts (treatment group) relative to federally funded projects. On the other hand, McCrary (2007) finds that court-ordered hiring quotas increased the fraction of African Americans among newly hired police officers while city crime rates appear unaffected.

Are the price effects large? They are comparable in magnitude to Marion (2009) and also to hedonic estimates in the boundary discontinuity design literature. Bayer et al. (2007) estimate that a one standard deviation in average test score leads to a 1.8% increase in monthly housing cost (relative to monthly user cost) and a $10,000 increase in the average income of households in a census block group leads to a 4.8% increase in monthly housing cost.

Furthermore, costs of ethnic-based restrictions are more likely to arise in settings with heterogeneous products and preferences that are heterogeneous by ethnic groups (eg. segregation preferences). The positive price effects for Chinese quotas suggest markets are thin given Chinese buyers' preferences. How thin is the housing market in Singapore? Tu and Wong (2002) reports that the volume of annual transactions in the resale market is 5% of the existing public housing stock. This is comparable to other studies of thin markets.[27] That there is a premium for Chinese-constrained units is not that surprising. We can think of the quota policy as reducing the stock of units available to Chinese buyers (they cannot buy units in constrained locations from non-Chinese). On average, 10% of the units are Chinese-constrained and only 13% of these units are owned by non-Chinese. This seems like a fairly small reduction in the stock but is potentially large when compared to the share of the stock that trades annually (5%).

One concern is that Chinese-constrained units are unobservably higher quality than unconstrained units. If this is the case, then, we would still find price differences even if there were no quota restrictions. It is unlikely that this premium is driven by omitted variables only. First, I find statistically significant price effects even after controlling for neighborhood fixed effects (equivalent to controlling for locational rents at the census block group level). If the quota restrictions had no impact, and Chinese-constrained units are of higher quality, then, we should not see more price dispersion for Chinese-constrained units and the proportion of units sold are also unlikely to be lower for Chinese-constrained units.

6 Conclusion

Many desegregation policies take the form of quotas but it is hard to find the data to evaluate these policies because they are either not available publicly or there are not enough

[27] For example, a study of trading frictions in the market for aircrafts, Gavazza (2011), reports that only 5.8% of the total stock of aircrafts in his sample traded within 12 months.

observations close to the quota limits. This paper uses a hand-collected dataset to study the impact of the ethnic housing quotas in Singapore. I show that the quota could lead to non-random sorting around the cutoffs in such a way that households of different ethnicities would bunch on opposite sides of the quota cutoff. However, manipulation of treatment status that leads to bunching around the quota cutoffs is hard if there are frictions in the market. Even if there were selection effects, they cannot fully account for the results I find.

In a decentralized equilibrium, the first best allocation of ethnic groups may not be achieved because of externalities. An individual chooses the neighborhood that maximizes his own utility, without internalizing the effect of his choice on the ethnic proportions in the neighborhood. Therefore, quotas could lead to welfare improvements by preventing extremely segregated outcomes. Wong (2012) finds that 30% of the neighborhoods in Singapore are within one standard deviation of the first best allocation of ethnic groups, where the first best was simulated using a utilitarian social welfare function and preference estimates from a structural location choice model.

In this paper, I built a theoretical framework to illustrate how the quota restrictions could lead to costs because of thin markets. In a Walrasian market with homogeneous products and homogeneous preferences, we would not expect any effects on prices and proportion of units sold. There would be no price discrimination mechanism because preferences are not different by ethnic groups and there would be no premiums for Chinese-constrained units.

My results illustrate how costs can arise from imposing group-based restrictions, especially if preferences are heterogeneous across these groups (markets are likely to be thin in this case). In Singapore, even though the policy was designed to affect as few households as possible, I found moderate price effects similar in magnitude to Marion (2009) and large effects on the proportion of units sold. My theoretical framework shows that these results are most consistent with preferences for segregation and thin markets for Chinese buyers. The estimates in this paper complement the welfare simulations and will be useful for cost benefit analyses of similar programs.

In future work, it would be useful to have prices by buyer and seller ethnicity. While the effects on average prices are moderate, price effects around the Chinese quota are opposite for Chinese and non-Chinese buyers. Therefore, it is possible that price effects are large by ethnic group but they cancel out when we examine average prices. Another caveat is that the estimates are local to the quota cutoffs and are identified off of marginal households close to the quota cutoffs. Finally, another important outcome to look at would be the time the property stays on the market.

References

Altonji, J. G., Elder, T. E., and Taber, C. R. (2005). Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools. *Journal of Political Economy*, 113(1):151–184.

Angrist, J. and Lavy, V. (1999). Using Maimonides' Rule to Estimate the Effect of Class Size on Scholastic Achievement. *Quarterly Journal of Economics*, 114(2):533–575.

Arnott, R. (1989). Housing vacancies, thin markets, and idiosyncratic tastes. *The Journal of Real Estate Finance and Economics*, 2(1):5–30.

Bajari, P. and Kahn, M. E. (2005). Estimating Housing Demand with an Application to Explaining Racial Segregation in Cities. *Journal of Business and Economic Statistics*, 23(1):20–33.

Banhardt, S. (2009). *Near and Dear? Evaluating the Impact of Neighbor Diversity on Inter-Religious Attitues*. PhD thesis, Harvard University.

Bayer, P., Ferreira, F., and McMillan, R. (2007). A Unified Framework for Measuring Preferences for Schools and Neighborhoods. *Journal of Political Economy*, 115(4):588–638.

Bayer, P., McMillan, R., and Rueben, K. (2004). An Equilibrium Model of Sorting in an Urban Housing Market. NBER Working Paper No. 10865.

Becker, G. S. (1971). *The Economics of Discrimination*. Chicago: Univ. Chicago Press, second edition.

Benabou, R. (1993). Workings of a City: Location, Education, and Production. *The Quarterly Journal of Economics*, 108(3):619–652.

Berry, S. T. (1994). Estimating Discrete-Choice Models of Product Differentiation. *The Rand Journal of Economics*, 25(2):242–262.

Berry, S. T., Levinsohn, J., and Pakes, A. (1995). Automobile Prices in Market Equilibrium. *Econometrica*, 63(4):841–890.

Bertrand, M., Hanna, R., and Mullainathan, S. (2010). Affirmative Action in Education: Evidence from Engineering College Admissions in India. *Journal of Public Economics*, 94(1-2):16–29.

Boisjoly, J., Duncan, G., Kremer, M., Levy, D., and Eccles, J. (2006). Empathy or Antipathy? The Impact of Diversity. *American Economic Review*, 96(5):1890–1905.

Card, D., Lee, D., and Pei, Z. (2009). Quasi-Experimental Identification and Estimation in the Regression Kink Design. Working Paper No. 553, Princeton University Industrial Relations Section.

Card, D., Mas, A., and Rothstein, J. (2008). Tipping and the Dynamics of Segregation. *Quarterly Journal of Economics*, 123(1):177–218.

Casas-Arce, P. and Saiz, A. (2011). Women and power: Unwilling, ineffective, or held back? IZA Discussion Papers 5645, Institute for the Study of Labor (IZA).

Chattopadhyay, R. and Duflo, E. (2004). Women as Policy Makers: Evidence from a Randomized Policy Experiment in India. *Econometrica*, 72(5):1409–1443.

Corporate Women Directors International (2012). Europe beats u.s. naming women to bank boards. Technical report, Corporate Women Directors International.

Cutler, D. M., Glaeser, E. L., and Vigdor, J. L. (1999). The Rise and Decline of the American Ghetto. *Journal of Political Economy*, 107(3):455–506.

Dutch Refugee Council (1999). Housing for refugees in the european union. Technical report, Dutch Refugee Council.

Edin, P.-A., Fredriksson, P., and Åslund, O. (2003). Ethnic Enclaves and the Economic Success of Immigrants-Evidence from a Natural Experiment. *Quarterly Journal of Economics*, 118(1):329–357.

Epple, D. and Sieg, H. (1997). Estimating Equilibrium Models of Local Jurisdictions. *Journal of Political Economy*, 107(4):645–681.

Finder, A. (March 20, 1988). The region: Pro & con: On racial quotas in housing; on discrimination in the cause of integration. *New York Times*, 0:0.

Gabriel, S. and Rosenthal, S. (1989). Household Location and Race: Estimates of a Multinomial Logit Model. *The Review of Economics and Statistics*, 71(2):240–249.

Gavazza, A. (2011). The role of trading frictions in real asset markets. *American Economic Review*, 101(4):1106–43.

Genesove, D. and Mayer, C. (2001). Loss aversion and seller behavior: Evidence from the housing market. *The Quarterly Journal of Economics*, 116(4):1233–1260.

Hahn, J., Todd, P., and van der Klaauw, W. (2001). Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design. *Econometrica*, 69(1):201–209.

Hårsman, B. and Quigley, J. (1995). The Spatial Segregation of Ethnic and Demographic Groups: Comparative Evidence from Stockholm and San Francisco. *Journal of Urban Economics*, 37(1):1–16.

Hendel, I., Nevo, A., and Ortalo-Magne, F. (2009). The relative performance of real estate marketing platforms: Mls versus fsbomadison.com. *American Economic Review*, 99(5):1878–98.

Housing Development Board (2006). *Annual Report*. Singapore: HDB.

Ihlanfeldt, K. and Scafidi, B. (2002). Black Self-Segregation as a Cause of Housing Segregation: Evidence from the Multi-City Study of Urban Inequality. *Journal of Urban Economics*, 51(2):366–390.

Imbens, G. and Lemieux, T. (2008). Regression Discontinuity Designs: A Guide to Practice. *Journal of Econometrics*, 142(2):615–635.

Lai, A. E. (1995). *Meanings of Multiethnicity: A Case Study of Ethnicity and Ethnic Relations in Singapore*. Oxford University Press.

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

Leonard, J. S. (1984). The impact of affirmative action on employment. *Journal of Labor Economics*, 2(4):439–463.

Levitt, S. D. and Syverson, C. (2008). Market distortions when agents are better informed: The value of information in real estate transactions. *The Review of Economics and Statistics*, 90(4):599–611.

Lum, S. K. and Tien, T. M. (2003). Integrating Differentials: A Study on the HDB Ethnic Integration Policy. *Crestimes, Singapore Center for Real Estate* (*CRES*), 3(1):5.

Marion, J. (2009). How costly is affirmative action? government contracting and california's proposition 209. *The Review of Economics and Statistics*, 91(3):503–522.

McCrary, J. (2007). The Effect of Court-Ordered Hiring Quotas on the Composition and Quality of Police. *American Economic Review*, 97(1):318–353.

McCrary, J. (2008). Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test. *Journal of Econometrics*, 142(2):698–714.

McFadden, D. (1973). Conditional Logit Analysis of Qualitative Choice Behavior. In Zarembka, P., editor, *Frontiers in Econometrics*. Academy Press, New York.

McFadden, D. (1978). Modelling the Choice of Residential Location. In Karlqvist, A., editor, *Spatial Interaction Theory and Planning Models*. North-Holland, New York.

Nechyba, T. J. and Strauss, R. P. (1998). Community Choice and Local Public Services: A Discrete Choice Approach. *Regional Science and Urban Economics*, 28(1):51–73.

Ong, S. E. and Koh, Y. C. (2000). Time on-market and price trade-offs in high-rise housing sub-markets. *Urban Studies*, 37:2057–2071.

Pancs, R. and Vriend, N. J. (2007). Schelling's Spatial Proximity Model of Segregation Revisited. *Journal of Public Economics*, 91(1-2):1–24.

Parliamentary Debates (1989). Official Report, 16 February. Singapore.

Parliamentary Debates (2003). Official Report, 10 November. Singapore.

Quigley, J. M. (1985). Consumer Choice of Dwelling, Neighborhood, and Public Services. *Regional Science and Urban Economics*, 15(1):41–63.

Quigley, J. M. (2002). Transactions costs and housing markets. Berkeley Program on Housing and Urban Policy, Working Paper Series qt6pz8p6zt, Berkeley Program on Housing and Urban Policy.

Rosenbaum, J. (1995). Changing the Geography of Opportunity by Expanding Residential choice: Lessons from the Gautreaux Program. *Housing Policy Debate*, 6(1):231–269.

Rothstein, J. and Yoon, A. H. (2008). Affirmative action in law school admissions: What do racial preferences do? NBER Working Papers 14276, National Bureau of Economic Research, Inc.

Schelling, T. C. (1971). Dynamic Models of Segregation. *Journal of Mathematical Sociology*, 1(3):143–186. (Abbreviated version appeared as "Models of Segregation" in *American Economic Review* 59(2), May 1969).

Singapore Department of Statistics (2000). Key Indicators of the Resident Population.

Singapore Department of Statistics (2006). Singapore Resident Population, 1990 - 2006.

Tiebout, C. M. (1956). A Pure Theory of Local Expenditures. *Journal of Political Economy*, 64(5):416–424.

Tu, Y. and Wong, G. K. (2002). Public policies and public resale housing prices in singapore. *International Real Estate Review*, 5:115–132.

Wong, M. (2012). Estimating the Impact of the Ethnic Housing Quotas in Singapore. forthcoming at Review of Economic Studies.

World Bank (2005). Implementing affirmative action in public services: Comparative administrative practice. Technical report, World Bank.

Table 1
Neighborhood and block level ethnic quotas [a]

	Neighborhood quotas	Block quotas	National proportion (2000)
Chinese	84%	87%	77%
Malay	22%	25%	14%
Indian	10%	13%	8%

[a] Source: 2000 Census (Singstat), Lum and Tan (2003)

Table 2
The relationship between quotas, buyer and seller ethnicities, and prices

Binding quota	Buyer ethnicity	Seller ethnicity	Status
Chinese	Chinese	Chinese	Allowed
	Non-Chinese	Non-Chinese	Allowed
	Non-Chinese	Chinese	Allowed
	Chinese	Non-Chinese	Not Allowed
Malay	Malay	Malay	Allowed
	Non-Malay	Non-Malay	Allowed
	Non-Malay	Malay	Allowed
	Malay	Non-Malay	Not Allowed
Indian	Indian	Indian	Allowed
	Non-Indian	Non-Indian	Allowed
	Non-Indian	Indian	Allowed
	Indian	Non-Indian	Not Allowed

Table 3
Summary statistics

Variable	N	Mean	Std. Dev.	Min	Max	Level	Description
Price	35744	234016	71943	40000	635000	Transaction	Transaction price (Singapore dollars, 1 USD=1.62 SGD as of Mar 2005)
Flat type sold	35744	4	1	1	8	Transaction	Flat type sold
Age	35744	18.20	9.24	3.00	40.00	Transaction	Age of flat sold
Chinese Quota	133378	0.11	0.31	0	1	Month-Block	Whether Chinese quota binds
Malay Quota	133378	0.12	0.32	0	1	Month-Block	Whether Malay quota binds
Indian Quota	133378	0.22	0.41	0	1	Month-Block	Whether Indian quota binds
Percent Sold	7222	4.99%	3.02%	0.34%	50.00%	Block	Percent of units in a block that was sold within the sample period
Percent Chinese	8007	77.91%	10.64%	0.00%	100.00%	Block	Percent of Chinese in a block
Percent Malay	8007	13.81%	9.40%	0.00%	100.00%	Block	Percent of Malay in a block
Percent Indian	8007	8.28%	5.55%	0.00%	83.33%	Block	Percent of Indian in a block
Percent Type 1	8007	0.05%	1.78%	0.00%	99.24%	Block	Percent of units in a block that is Type 1
Percent Type 2	8007	0.97%	8.26%	0.00%	100.00%	Block	Percent of units in a block that is Type 2
Percent Type 3	8007	23.42%	36.78%	0.00%	100.00%	Block	Percent of units in a block that is Type 3
Percent Type 4	8007	37.63%	34.07%	0.00%	100.00%	Block	Percent of units in a block that is Type 4
Percent Type 5	8007	24.88%	32.07%	0.00%	100.00%	Block	Percent of units in a block that is Type 5
Percent Type 6	8007	12.97%	32.24%	0.00%	100.00%	Block	Percent of units in a block that is Type 6
Percent Type 7	8007	0.01%	1.12%	0.00%	100.00%	Block	Percent of units in a block that is Type 7
Percent Type 8	8007	0.08%	2.62%	0.00%	100.00%	Block	Percent of units in a block that is Type 8

Table 4
Testing differences in proportion of unit types[a]

Quota	Chinese		Malay		Indian	
Sample	Pre- and Post- Quota	Pre-Quota Only	Pre- and Post- Quota	Pre-Quota Only	Pre- and Post- Quota	Pre-Quota Only
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Proportion of type 3	-0.00263	-.0796***	0.00721	-0.0124	-.0273***	-.0403***
	(.0156)	(.018)	(.0124)	(.0145)	(.00943)	(.00993)
Proportion of type 4	.0456***	.0312*	-0.0131	0.00716	.0189**	.0215**
	(.0153)	(.0173)	(.0121)	(.0134)	(.00892)	(.0093)
Proportion of type 5	0.0102	.0518***	-0.00826	-0.01010	-0.00209	0.00383
	(.0147)	(.0162)	(.0109)	(.0119)	(.00818)	(.00861)
Proportion of type 6	-.061***	-0.0111	.0204*	.0206*	.0155*	.0207**
	(.0123)	(.0125)	(.0114)	(.0119)	(.00914)	(.00891)
Observations	71713	63232	53008	45887	113985	107194

[a] The regression equation is $y_{bk} = \alpha + \beta\, QC_{bkt} + \Sigma^{4}_{l=1}\, \varphi_l (percentC_{bk} - 0.87)^l + \varepsilon_{bkt}$ where y_{bk} is the outcome variable (*proportion type 3, proportion type 4, proportion type 5, proportion type 6* units in each block *b*, town *k*; QC_{bkt} is a dummy that is *1 if the Chinese quota is binding in month t*; $(percentC_{bk} - 0.87)^l$ are l^{th} order polynomials of *percent Chinese*, centered around the block quota cutoff. I repeat the exercise for the Malay quota and for the Indian quota. Columns 1, 3 and 5 report results using all blocks that are within 10% of the Chinese, Malay, and Indian quota cutoffs, respectively. Columns 2, 4 and 6 report results using only the blocks that were built before the policy started in1989. Standard errors are in parentheses and clustered at the block level. ***Statistically significant at 1%. **Statistically significant at 5%. *Statistically significant at 10%.

Table 5
Results of the quota impact on price[a]

Dependent variable	ln price (1)	ln price (2)	ln price (3)	ln price (4)	ln price (5)
Panel A: Chinese quota					
C	.081***	.0503***	.0502***	.0321***	-0.00413
	(.0166)	(.0102)	(.0104)	(.00664)	(.00872)
N	19533	19533	19533	19533	19533
R-squared	0.00926	0.798	0.799	0.825	0.892
Panel B: Malay quota					
M	-.0396***	-.0262***	-.027***	-.00697*	0.00564
	(.0116)	(.00762)	(.00803)	(.00374)	(.00635)
N	14921	14921	14921	14921	14921
R-squared	0.0039	0.747	0.748	0.776	0.846
Panel C: Indian quota					
I	-.0285***	-.0332***	-.0341***	-.0109**	0.00133
	(.0108)	(.0109)	(.0114)	(.00488)	(.00478)
N	32147	32147	32147	32147	32147
R-squared	0.00908	0.775	0.776	0.806	0.875
Ethnic proportions	Y	Y	Y	Y	N
Controls	N	Y	Y	Y	N
Month	N	Y	Y	Y	N
Town	N	Y	Y	N	N
Linear town-by-month trend	N	N	Y	N	N
Neighborhood	N	N	N	Y	N
Block	N	N	N	N	Y

[a] The regression equation is $lnPrice_{ibkt} = \alpha + \beta\, QC_{bk,t-1} + \Sigma^4_{l=1}\, \varphi_l (percentC_{bk} - 0.87)^l + \varepsilon_{ibkt}$ where $lnPrice_{ibkt}$ is the *log of the price of transaction i* in block *b*, town *k* and month *t*; $QC_{bk,t-1}$ is a dummy that is *1 if the Chinese quota is binding in the previous month*; $(percentC_{bk} - 0.87)^l$ are l^{th} order polynomials of *percent Chinese*, centered around the block quota. The controls are other observable characteristics of the block (*age of block*, its squared, *proportion of type 2 units*, *proportion of type 3 units*, *proportion of type 4 units*, *proportion of type 5 units*, *proportion of type 6 units*, *proportion of type 7 units*, *proportion of type 8 units*). I repeat the exercise for the Malay quota (Panel B) and for the Indian quota (Panel C). All specifications only use blocks that are within 10% of the Chinese, Malay, and Indian quota cutoffs, respectively. Standard errors are in parentheses, clustered at the block level (columns 1 and 5), town level (columns 2 and 3), neighborhood level (column 4). ***Statistically significant at 1%. **Statistically significant at 5%. *Statistically significant at 10%.

Table 6
Results of the quota impact on type of unit sold[a]

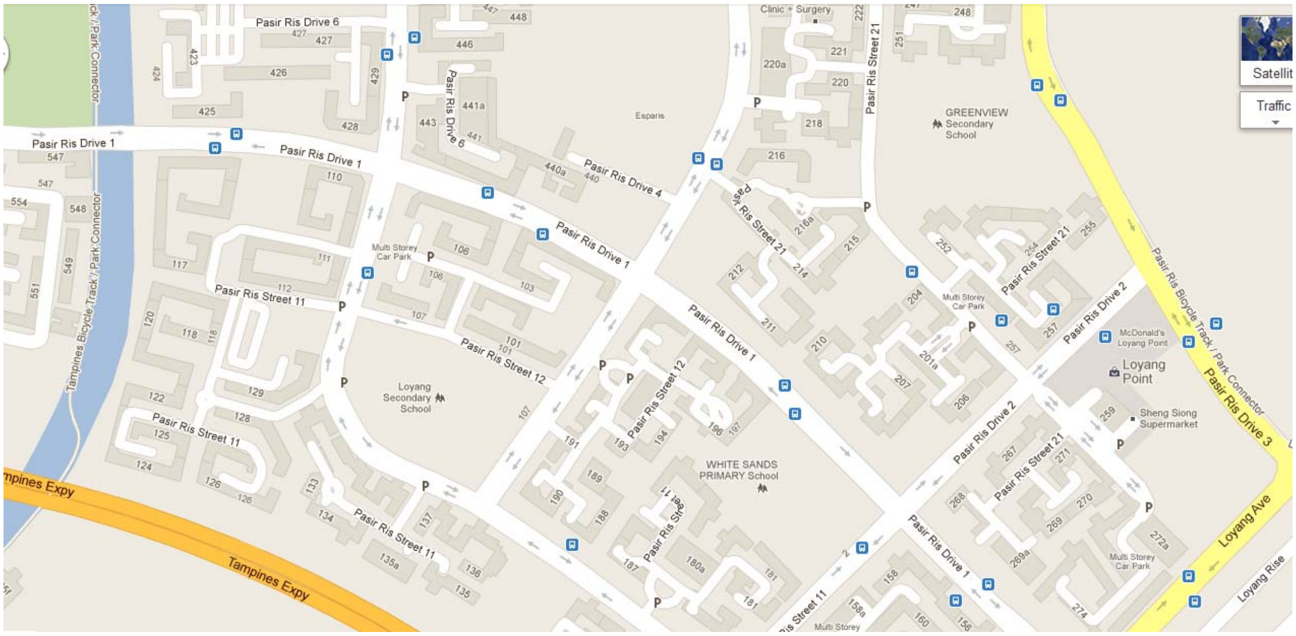
Quota Dependent variable	Chinese Flat Type Sold (1)	Malay Flat Type Sold (2)	Indian Flat Type Sold (3)
Quota dummy	-.0841*	-.0854*	0.0273
	(.0496)	(.0449)	(.0364)
Ethnic proportion	-1.56	1.99*	-2.79***
	(1.06)	(1.17)	(1.04)
(Ethnic proportion)^2	28.2	24.1	-39.7**
	(25)	(26.8)	(20.1)
(Ethnic proportion)^3	76.1	-140	291
	(200)	(179)	(191)
(Ethnic proportion)^4	-3134	-1830	6276**
	(3223)	(3149)	(2639)
Type 1	-2.92***	-2.2***	-3.06***
	(.312)	(.0675)	(.29)
Type 2	-2.25***	-.517***	-2.16***
	(.0801)	(.0461)	(.0515)
Type 3	-.406***	.596***	-.357***
	(.0379)	(.0423)	(.0339)
Type 4	.551***	1.54***	.623***
	(.034)	(.0479)	(.0329)
Type 5	1.51***	dropped	1.51***
	(.0391)		(.0372)
Type 6	3.52***	dropped	3.39***
	(.165)		(.128)
Type 7	3.65***	dropped	3.44***
	(.196)		(.14)
Observations	19533	14868	32147

[a] This is an ordered probit regression where the dependent variable is an integer between one and eight. The regressors are the same as column 1 of Table 5. All specifications only use blocks that are within 10% of the Chinese, Malay, and Indian quota cutoffs, respectively. Standard errors are in parentheses, clustered at the block level. ***Statistically significant at 1%. **Statistically significant at 5%. *Statistically significant at 10%.

Table 7
Results of the quota impact on the proportion of units sold[a]

Quota	Chinese			Malay			Indian		
Dependent variable	Proportion Sold	Proportion Sold	Proportion Sold	Proportion Sold	Proportion Sold	Proportion Sold	Proportion Sold	Proportion Sold	Proportion Sold
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Only blocks with resale transactions									
Probability quota binds	-.00544***	-.00456**	-.00625***	-.0102***	-.00647***	-.00348*	-.00623***	-.00466**	-0.00171
	(.00125)	(.00177)	(.00178)	(.00147)	(.00136)	(.00207)	(.000952)	(.00193)	(.00172)
N	3980	3980	3980	2906	2906	2906	6324	6324	6324
R-squared	0.0134	0.095	0.148	0.0172	0.121	0.188	0.0209	0.11	0.147
Panel B: Includes blocks without resale transactions									
Probability quota binds	-0.00195	-.00791***	-.00935***	-.00909***	-.0131***	-.00783***	-.00363***	-.00729**	-0.00135
	(.00127)	(.00147)	(.0019)	(.0016)	(.00237)	(.00236)	(.00102)	(.00307)	(.00181)
N	4347	3980	3980	3149	2906	2906	6818	6324	6324
R-squared	0.0109	0.0745	0.142	0.0103	0.097	0.181	0.00482	0.0863	0.137
Ethnic proportions	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	Y	N	Y	Y	N	Y	Y
Town	N	Y	N	N	Y	N	N	Y	N
Neighborhood	N	N	Y	N	N	Y	N	N	Y

[a] The regression equation is $pSold_{bk} = \alpha + \beta\ percentQC_{bk} + \Sigma^{4}_{l=1}\ \varphi_l percentC^{l}_{bk} + \varepsilon_{bk}$ where $pSold_{bk}$ is the proportion of units sold in block *b*, town *k*, aggregated across months; $percentQC_{bk}$ is the proportion of months the Chinese (C) quota is binding; $percentC^{l}_{bk}$ are l^{th} order polynomials of *percent Chinese*. All specifications only use observations within 10% of the quota cutoffs. I repeat the exercise for the Malay and for the Indian quotas. Standard errors in parentheses, clustered at the block level (columns 1, 4 and 7), town level (columns 2, 5 and 8) and neighborhood level (columns 3, 6 and 9). ***Statistically significant at 1%. **Statistically significant at 5%. *Statistically significant at 10%.



Source: Google Maps

FIG. 1. –Map of HDB blocks and HDB neighborhoods. Each number in the map corresponds to an HDB block. There are 4 HDB neighborhoods in this map. Neighborhood 1 comprises all HDB blocks between 100 and 199, neighborhood 2 comprises all HDB blocks between 200 and 299, neighborhoods 4 and 5 are defined in a similar manner.

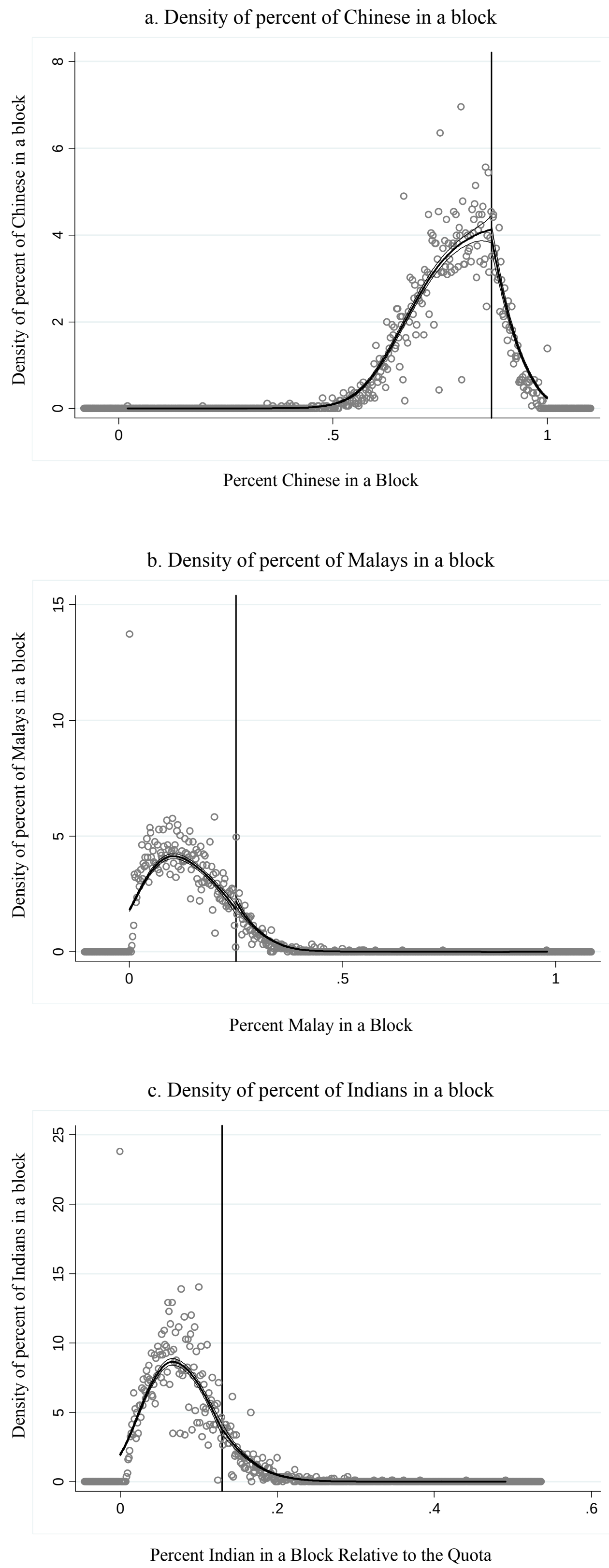
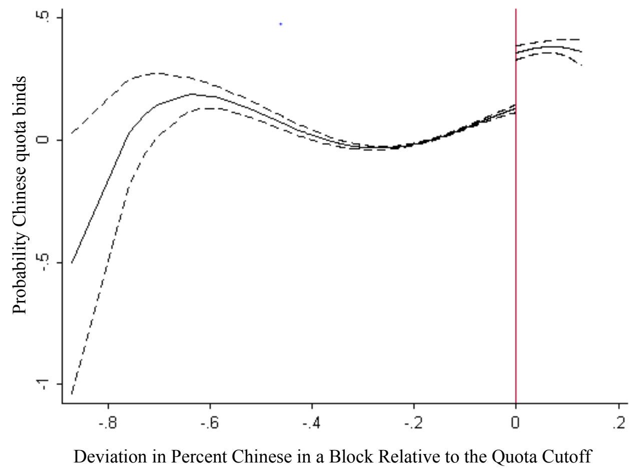
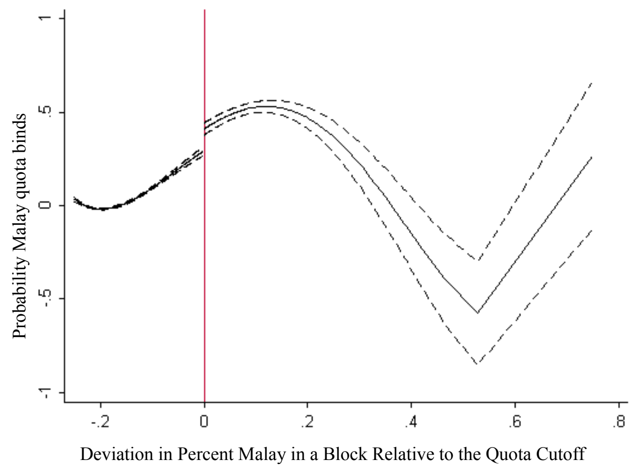


Fig. 2. Testing for discontinuities in the density of the running variable (ethnic proportions). The vertical lines correspond to the quota cutoffs.

a. Probability that the Chinese Quota Binds



b. Probability that the Malay Quota Binds



c. Probability that the Indian Quota Binds

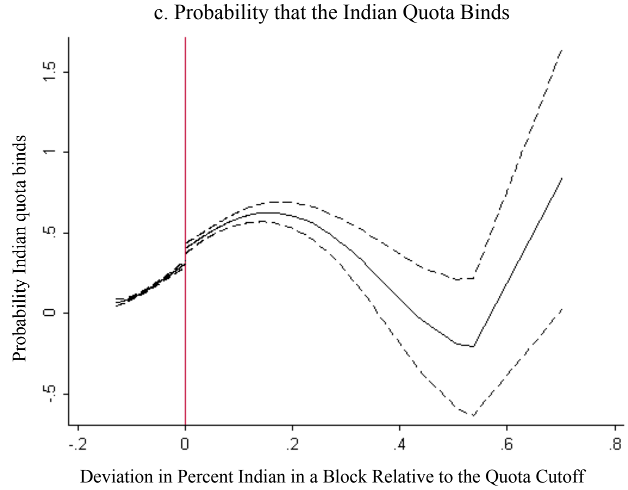
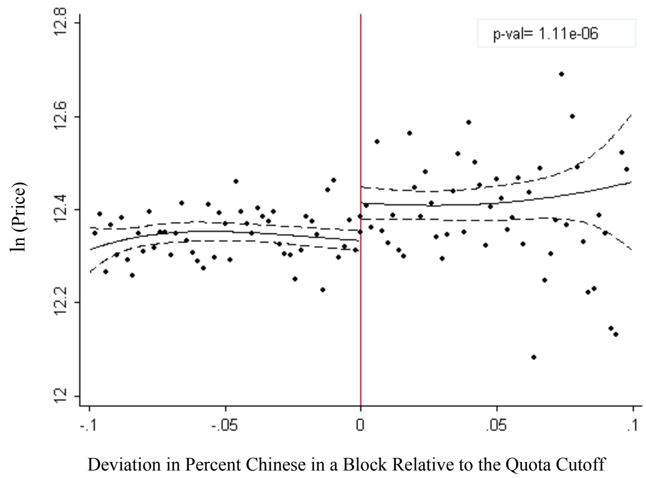
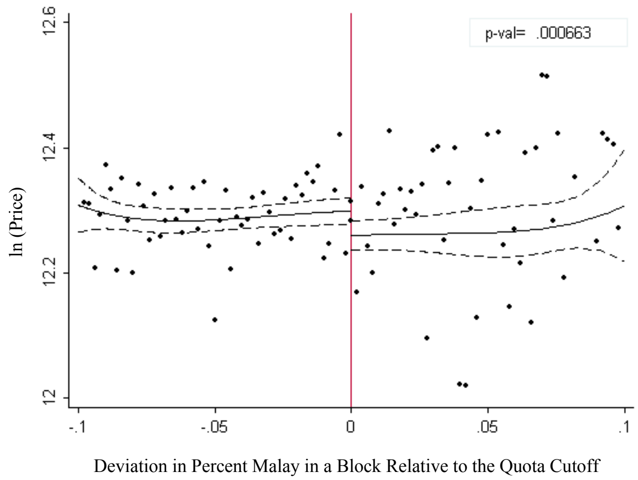


Fig. 3. Testing for discontinuity in the probability that the quota binds. Each panel in this figure is constructed by regressing Q_{bt} (*a dummy for whether the quota is binding for block b in month t*) on a dummy that is 1 when the ethnic proportions are above the block quota cutoff and 4th order polynomials of ethnic proportions, centered around the quota cutoffs, then plotting the predicted probabilities. Repeat the exercise for the Malay quotas and Indian quotas. The dashed lines represent 95% confidence intervals. Standard errors clustered at the block level. The coefficient estimates are 23%, 12% and 10% for Chinese, Malay and Indian quotas.

a. The Impact of Chinese Block Quotas on ln(price)



b. The Impact of Malay Block Quotas on ln(price)



c. The Impact of Indian Block Quotas on ln(price)

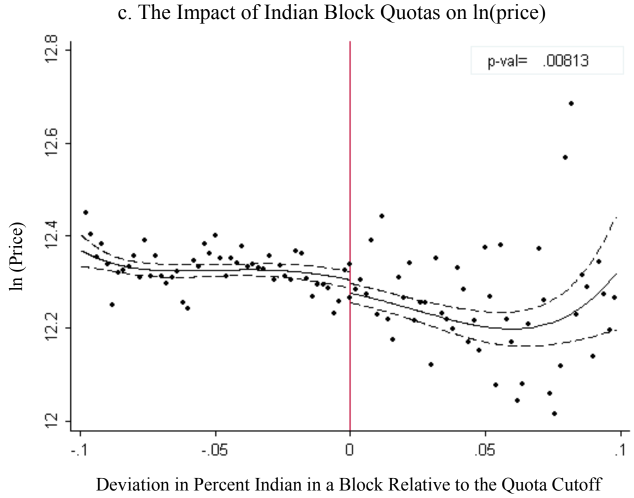


Fig. 4. Impact of block quotas on *lnPrice*, 10% above and below the quota cutoffs. Each panel in this figure is constructed using the following procedure for observations within 10% of the ethnic quota cutoffs: (i) regress the *log of transaction prices* on smooth functions of *ethnic proportions centered around the quota cutoffs* (4th order polynomials) and a dummy that is *1 when the corresponding block quota is binding in the previous month*; (ii) plot the predicted prices (solid line) as well as the 95% confidence interval (dashed lines); (iii) plot means of ln(price) for each 1% bin. I repeat the exercise for the Malay quotas and Indian quotas. Standard errors clustered at the block level. Reported p-values correspond to the hypothesis test that the discontinuity at the cutoff is 0. The coefficient estimates are 8.1%, -3.96% and -2.85% for the Chinese, Malay and Indian quotas.

Data Appendix

October 5, 2012

In this section, I discuss how I constructed the sample and some key variables.

Sample

I calculate ethnic proportions using phone listings in the 2005 phonebook. I use data on the name, street name, apartment block number and postal code. Each phonebook includes six-digit postal codes that uniquely identify an HDB block. The first two digits of the postal code identifies the postal sector. The postal sector together with the fourth digit of the postal code identifies the HDB neighborhood. There is also an indicator that identifies whether an address is an HDB address.

The phonebook has 795,208 listings. Each listing has an identifying number. I dropped 41,814 listings that appear to be duplicate listings (they share the same identifying numbers, name and address with other listings). I dropped 204,248 phone listings because the street address did not appear on the Ethnic Integration Policy website. I dropped 13 listings because the addresses did not correspond to HDB blocks. I dropped 1,109 listings because I could not match these names to ethnicities. The final sample includes 548,024 listings.

After matching names to ethnicities, I collapsed the data to the HDB block level and obtained 8,042 blocks. I merged these blocks to the HDB census data using street names and block numbers. I dropped 35 blocks because I was not able to match addresses in the phonebook to the HDB census (this represents fewer than 2000 phone listings). The final sample includes 8,007 blocks.

Transactions data

I downloaded 35,942 resale transactions between April 2005 and August 2006. I dropped 198 transactions because the street address could not be merged with the street addresses in the HDB census.

Quota data

Of the 133,378 block-months in the quota data, I filled 117 observations by comparing the quota status in the previous and the following months. I checked that the quota status for all 117 observations was the same the month before and the month after and filled in the missing quota status using the quota status for the month before.

Appendix Tables

Table A1 Results of the quota impact on price (separate polynomials for constrained and unconstrained blocks)[a]

Dependent variable	ln price (1)	ln price (2)	ln price (3)	ln price (4)	ln price (5)
Panel A: Chinese quota					
C	.069***	.041***	.041***	.0237***	-0.00413
	(.023)	(.00886)	(.00895)	(.0074)	(.00872)
N	19533	19533	19533	19533	19533
R-squared	0.0145	0.798	0.799	0.825	0.892
Panel B: Malay quota					
M	-.0525***	-.0342***	-.0348***	-.0183***	0.00564
	(.0177)	(.0046)	(.00464)	(.00602)	(.00635)
N	14921	14921	14921	14921	14921
R-squared	0.00519	0.747	0.749	0.777	0.846
Panel C: Indian quota					
I	-0.0166	-.0304**	-.0313**	-0.00862	0.00133
	(.0154)	(.0119)	(.0122)	(.00572)	(.00478)
N	32147	32147	32147	32147	32147
R-squared	0.0111	0.775	0.776	0.806	0.875
Ethnic proportions	Y	Y	Y	Y	N
Controls	N	Y	Y	Y	N
Month	N	Y	Y	Y	N
Town	N	Y	Y	N	N
Town-trend	N	N	Y	N	N
Neighborhood	N	N	N	Y	N
Block	N	N	N	N	Y

[a] The regression equation is $lnPrice_{ibkt} = \alpha + \beta\, QC_{bk,t-1} + \Sigma^4_{l=1}\, \varphi_l (percentC_{bk} - 0.87)^l + \Sigma^4_{l=1} \gamma_l QC_{bk,t-1} * (percentC_{bk} - 0.87)^l + \varepsilon_{ibkt}$ where $lnPrice_{ibkt}$ is the *log of the price of transaction i* in block *b*, town *k* and month *t*; $QC_{bk,t-1}$ is a dummy that is *1 if the Chinese quota is binding in the previous month*; $(percentC_{bk} - 0.87)^l$ are l^{th} order polynomials of *percent Chinese*, centered around the block quota. The controls are other observable characteristics of the block (*age of block*, its squared, *proportion of type 2 units*, *proportion of type 3 units*, *proportion of type 4 units*, *proportion of type 5 units*, *proportion of type 6 units*, *proportion of type 7 units*, *proportion of type 8 units*). I repeat the exercise for the Malay quota (Panel B) and for the Indian quota (Panel C). All specifications only use blocks that are within 10% of the Chinese, Malay, and Indian quota cutoffs, respectively. Standard errors are in parentheses, clustered at the block level (columns 1 and 5), town level (columns 2 and 3), neighborhood level (column 4). ***Statistically significant at 1%. **Statistically significant at 5%. *Statistically significant at 10%.

Table A2 Results of the quota impact on type of unit sold (separate polynomials for constrained and unconstrained blocks)[a]

Quota	Chinese	Malay	Indian
Dependent variable	Flat Type Sold	Flat Type Sold	Flat Type Sold
	(1)	(2)	(3)
Quota dummy	-.0841*	-.0854*	0.0273
	(.0496)	(.0449)	(.0364)
Ethnic proportion	-1.56	1.99*	-2.79***
	(1.06)	(1.17)	(1.04)
(Ethnic proportion)^2	28.2	24.1	-39.7**
	(25)	(26.8)	(20.1)
(Ethnic proportion)^3	76.1	-140	291
	(200)	(179)	(191)
(Ethnic proportion)^4	-3134	-1830	6276**
	(3223)	(3149)	(2639)
Type 1	-2.92***	-2.2***	-3.06***
	(.312)	(.0675)	(.29)
Type 2	-2.25***	-.517***	-2.16***
	(.0801)	(.0461)	(.0515)
Type 3	-.406***	.596***	-.357***
	(.0379)	(.0423)	(.0339)
Type 4	.551***	1.54***	.623***
	(.034)	(.0479)	(.0329)
Type 5	1.51***	dropped	1.51***
	(.0391)		(.0372)
Type 6	3.52***	dropped	3.39***
	(.165)		(.128)
Type 7	3.65***	dropped	3.44***
	(.196)		(.14)
Observations	19533	14868	32147

[a] This is an ordered probit regression where the dependent variable is an integer between one and eight. The regressors are the same as column 1 of Table A1. All specifications only use blocks that are within 10% of the Chinese, Malay, and Indian quota cutoffs, respectively. Standard errors are in parentheses, clustered at the block level. ***Statistically significant at 1%. **Statistically significant at 5%. *Statistically significant at 10%.