

Estimating the Impact of the Ethnic Housing Quotas in Singapore

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Abstract

Desegregation is a key policy issue in many countries with diverse populations. These are typically nation-wide policies that affect many households but we know little about their impact because the data is hard to obtain. By hand-matching 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. I estimate statistically significant quota causes discontinuities in the price, quality and quantity of units sold in apartment blocks just above the quota limits, compared to units below the quota limits. Chinese-constrained units are more expensive even though they are of significantly lower quality than the unconstrained units. Conversely, Indian-constrained units are cheaper but of higher quality. Malay-constrained units that were sold are cheaper and of lower quality. In addition to these effects on the price and quality margin, I also find that constrained units are harder to sell. I show that selection effects cannot fully account for these discontinuities.

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1 Introduction

The seminal work by Thomas Schelling showed that private location decisions can affect the utility of neighbors by altering neighborhood compositions, leading to the famous result of neighborhoods tipping even when individuals desire heterogeneous neighborhoods (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 such desegregation policies take the form of quotas that limit the group composition in housing markets, schools and the workplace, including court-ordered racial hiring quotas in municipal police departments in the US, affirmative action quotas in Indian colleges and ethnic housing quotas in Singapore. Understanding the causal impact of these quota policies is important because they potentially affect many individuals.

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 forced the ethnic proportions of these blocks and neighborhoods farther above the upper limit, however, would be 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.

To circumvent the problem that quota-constrained and quota-unconstrained locations are not comparable, I adopt an empirical framework similar to the regression kink design (RKD) in Card, Lee, and Pei (2009). The strategy is to identify kinks in the outcome variable that coincide 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, Todd, and van der Klaauw, 2001), it does not fit within a standard regression discontinuity design (RDD) framework (Imbens and Lemieux, 2008; Lee and Lemieux, 2010) because the assignment variable/running variable of interest (ethnic proportions) is endogenous.² Therefore, the identification strategy is more similar to Card, Lee, and Pei (2009)'s study on the impact of previous earnings (an endogenous running variable) on unemployment

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

²To implement RDD, I would need pre-policy data on ethnic proportions. The quota policy was announced in 1989 and implemented within 3 weeks. Therefore, it is likely ethnic proportions just before 1989 were exogenous. Unfortunately, I was not able to obtain the pre-policy data.

insurance benefits.

There is a vast empirical literature on the causes and consequences of residential segregation (Bajari and Kahn, 2005; Bayer, McMillan, and Rueben, 2004; Card, Mas, and Rothstein, 2008; Cutler, Glaeser, and Vigdor, 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, Duncan, Kremer, Levy, and Eccles, 2006; Edin, Fredriksson, and Åslund, 2003; Rosenbaum, 1995). This is largely due to two challenges that I am able to circumvent. First, many desegregation policies impose strict limits on neighborhood composition. 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. Therefore, it is possible to observe housing transactions that are above the upper limits of the quota. To this day, there exist many units above the quota limits and both Chinese and non-Chinese buyers are allowed to purchase units in Chinese-constrained locations. 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 offers 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 police departments in the US using event study analyses because “information on quotas is much more poorly measured than whether a city was litigated, and the date the litigation began” (p349). Bertrand, Hanna, and Mullainathan (2010) administered a large-scale 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 589,000 names to ethnicities using the

Singapore Residential Phonebook. This allows me to calculate ethnic proportions for each of the 8000 apartment blocks (an average of 70 households). I combined this data with other outcomes that I downloaded quarterly from housing transactions data on the HDB website.

One identification assumption behind the regression kink design (and regression discontinuity design as well) is that individuals cannot precisely sort around the quota limits so that variation in the treatment status around the policy cutoff is “as good as randomized.” This assumption fails if there exists bunching around the quota limits. I show that 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 the propensity to upgrade housing units, price effects found at the quota cutoff could be due to a comparison of upgraded versus not 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). I find that 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, I find that the bunching pattern around the Malay quotas is not consistent with households trying to “precisely sort” around the cutoffs, as discussed in Lee and Lemieux (2010). I return to this in the results section.

Using data within 10 percent of the cutoffs, I find that Chinese-constrained units are 4 to 7% more expensive than unconstrained units that are close to, but below the quota limit. The magnitude of this discontinuity represents 4 to 7 times the median monthly income of the Chinese (S\$2,335).³ Malay-constrained units are 3 to 5% cheaper and Indian-constrained units are 2 to 3% cheaper. In terms of monthly income, these discontinuities are 4 to 7 times the median monthly income of the Malays (S\$1,790) and 2 to 3 times the median monthly income of the Indians (S\$2,167). All these price discontinuities at the quota cutoffs are statistically significant at the 5% and 1% level even after controlling for month and town fixed effects and block level controls that explain up to 80% of the variation in public housing prices.

The result on prices is interesting when compared to the results on the quality of the units sold. I find that Chinese-constrained units that are sold are of worse quality even though the prices are higher. Conversely, Indian-constrained units are of significantly better quality even though the prices of those units are lower. Malay-constrained units that are sold are of lower quality, consistent with the finding that the prices of these units are also lower. In addition to the price and quality margin, I also look at the quantity of units sold. An increase in the number of months that a quota binds significantly decreases the proportion of units sold for all quotas. On average, the Chinese and Malay quota bind for 2 months and the Indian quota binds for 4 months. At these averages, the proportion of

³Calculated using the average price of units sold (S\$240,000).

units sold is lower by 2% for the Chinese, Malay and Indian quotas. On average, only 0.2% of units are sold in a month. These estimates represent an increase in the time-to-sell margin by 10 months.

Below, I discuss the background of the policy (Section 2), describe the data (Section 3), discuss estimation (Section 4), the results (Section 5) and conclude.

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). There are three ways Singapore residents can live in a HDB unit. They may apply through the primary allocation system for new HDB units, they may purchase existing HDB units in the resale market or they may rent. The rental market is negligible: 98% of the HDB units are owner-occupied (Housing Development Board, 2006). This paper focuses on the resale market which is the relevant market for the ethnic quotas. Relative to the primary market which is heavily regulated, the resale market functions as an open market.

Public housing was first built in Singapore in 1960 to solve the young nation's housing crisis (Parliamentary Debates, 1989). To cater to the different needs of households, HDB designed and built 8 unit types. Type 1 was a studio, Type 2 meant a 1-bedroom unit, Type 3 was 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 homogenous.

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*. A group of HDB units constitute an HDB *block*. A group of HDB blocks make up a *neighborhood*. 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. The

average neighborhood in Singapore has 4000 households and an average land area of 1.5 square miles and the average HDB block has 70 households.

The government of Singapore introduced the Ethnic Integration Policy to address the "problem" of the increase in the "concentrations of racial groups" in HDB estates (Parliamentary Debates, 1989).⁴ The policy was announced in a parliamentary debate on February 16, 1989 and was implemented starting March 1, 1989. It is a set of quota limits at the block and neighborhood level. Table 1 lists the quotas, in comparison to the 2000 national ethnic proportions. Neighborhood quotas are 2% to 8% above the national ethnic proportions in 2000. Block quotas are 3% above the neighborhood quotas, allowing more flexibility at the block level because blocks can be more segregated than neighborhoods. In practice, the HDB did not want to evict owners in existing units that were in violation of the quotas. To this day, there exist blocks and neighborhoods whose ethnic proportions exceed the quota limits.

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.⁵ 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 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.

2.1 Price effects at the quota limits

I discuss the price effects around the Chinese quota only. The effects for Malay and Indian quotas are similar. To maximize profits, sellers will always sell to the highest bidder. So, what happens to prices around the cutoffs depends on the distribution of the maximum bids by Chinese and non-Chinese buyers. Around the Chinese quota limit, the impact on Chinese and non-Chinese-owned units will be different.

Units owned by *non-Chinese* that are right at or above the quota limit will likely sell for less compared to units right below the quota limit if Chinese buyers are willing to pay more than non-Chinese buyers to live in Chinese neighborhoods. This is because

⁴Racial harmony is important in Singapore because of violent racial riots in the 1960s.

⁵These 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.

the quota policy does not allow non-Chinese sellers to sell Chinese-constrained units to Chinese buyers even if they are the highest bidders. Conversely, non-Chinese owners of unconstrained units can sell to the highest bidder, regardless of the ethnicity of the bidder. The magnitude of the price difference will depend on the distribution of maximum bids by the Chinese and non-Chinese buyers.

Units owned by *Chinese* that are right at or above the quota limit will likely sell for more. According to the policy, Chinese sellers are not affected by the quota because they can sell to both Chinese and non-Chinese buyers. But Chinese buyers can only buy a unit in a Chinese-constrained location from a Chinese seller. If markets were thin (due to search frictions, for example), Chinese buyers may be willing to pay strictly more for a Chinese-owned unit in a quota-constrained location rather than wait and search for a similar unit in an unconstrained location. With thick markets, this premium for Chinese-owned units right above the quota limit will be bid towards zero because Chinese buyers can costlessly find similar units right below the quota limit.

Note that forward-looking behavior could 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 rather than a discrete jump upwards in prices at 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%.

In summary, depending on the distribution of bids by Chinese and non-Chinese buyers, the impact of the quota on prices (measured by the price difference right above and right below the quota limit) will likely be *weakly negative* for *non-Chinese-owned units* and *weakly positive* for *Chinese-owned units*.

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 an 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.⁶ 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

⁶For more details on what “precise sorting” means, see Lee and Lemieux (2010)

non-upgraded units below the cutoff.

3 Data

To estimate the effects discussed in the previous section, I collected data on 35,718 actual transaction prices from the HDB website between April 2004 and November 2006. From the same website, I downloaded monthly data on the quota status of apartment blocks, between March 2003 and October 2006. I matched the quota status of the previous month to each transaction so that the quota status of block b in November 2005 was matched to the transaction price for units in the same block in December 2005.⁷

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 589,000 names to ethnicities using differences in the structure of Chinese, Malay and Indian names.⁸ 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. The match between names and ethnicity is likely to be most accurate for Chinese names because of distinct last names.⁹ 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 589,000 names in the phonebook, 470,000 were matched using popular first and last names and the remaining were matched individually. Of these, 40% were eventually matched as Chinese names, 28% and 32% were matched as Malays and Indians, respectively. As a check, my measure of ethnicity using names generates 78% "Chinese", 14% "Malays" and 8% "Indians", almost identical to the actual national proportions from the 2000 Census.

I have two datasets describing the distribution of housing by unit type. There are 8 unit types with varying degrees of quality. The first dataset is a non-public census of all HDB units listing the number of each type of unit in all HDB blocks. The second dataset lists the type of unit sold (downloaded monthly from the HDB website on resale transactions).

Table 3 lists the summary statistics of the full dataset. There are 8,067 blocks and 35,718 resale transactions. The Chinese and Malay quotas bind for one-tenth of the sample

⁷I repeated the analysis with a 3-month lag, instead of a 1-month lag and the main results are similar.

⁸The 2005 phonebook was published on April 1st 2005, and includes a total of 789,048 households. I only included households living in HDB blocks. Movers have to update their contact information within a month of moving. 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.

⁹Even Chinese Muslims would tend to keep their last names as a part of their Muslim names.

and the Indian quotas bind for one-fifth of the sample.

The dataset is a combination of monthly variables (monthly quota dummies and data on monthly transactions downloaded from the HDB website) as well as fixed variables (ethnic proportions from the phonebook and types of units in each HDB block). I do not observe the ethnicity of the buyer and the seller from the transactions data on HDB's website. Therefore, my empirical analysis will include prices, quantity and quality of units sold at the block-month level.

4 Estimation

The challenge in identifying the treatment effect is omitted variables. 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 was zero) because of omitted variables - areas with more Chinese amenities tend to attract more Chinese, so, are more likely to be Chinese-constrained and more expensive.

The kink in the policy rule at the cutoff 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 cutoff on ethnic proportions and units are constrained (the quota status is 1) above the cutoff.

My empirical framework is similar to the regression kink design (RKD) in Card, Lee, and Pei (2009). The strategy is to identify kinks in the outcome variable that coincide 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, Todd, and van der Klaauw, 2001), it does not fit within a standard regression discontinuity design (RDD) framework (Imbens and Lemieux, 2008; Lee and Lemieux, 2010) because the assignment variable/running variable of interest (ethnic proportions) is endogenous.¹⁰ Therefore, the identification strategy is more similar to Card, Lee, and Pei (2009)'s study on the impact of previous earnings (an endogenous running variable) on unemployment insurance benefits.

I estimate four sets of equations. I test for quota effects on 3 sets of outcomes: prices, the quality of units sold and the quantity of units sold. I restrict my analysis to observations within 10% of the Chinese, Malay and Indian block quotas respectively. The first three equations are at the month-block level and the final equation is at the block level. Recall that the dataset is comprised of monthly and fixed variables. All variables describing

¹⁰To implement RDD, I would need pre-policy data on ethnic proportions. The quota policy was announced in 1989 and implemented within 3 weeks. Therefore, it is likely ethnic proportions just before 1989 were exogenous. Unfortunately, I was not able to obtain the pre-policy data.

actual transactions (price, quality of units sold, quota dummies) are at the month-block level while all other variables (ethnic proportions, number of each unit type in a block) are fixed variables.

The first equation tests if there is in fact a step function in the probability of the quota binding.

$$QC_{bit} = \alpha + \beta 1(\text{percent}C_{bi} \geq 0.87) + \sum_{k=1}^4 \phi_k (\text{percent}C_{bi} - 0.87)^k \quad (1)$$

$$+ \sum_{k=1}^4 \gamma_k 1(\text{percent}C_{bi} \geq 0.87) * (\text{percent}C_{bi} - 0.87)^k + \varepsilon_{bit}$$

where QC_{bit} is a dummy for whether the (C)hinese quotas are binding for units in block b , town i and month t (this is the assignment dummy obtained directly from the HDB data on quotas), $1(\text{percent}C_{bi} \geq 0.87)$ is a dummy for whether the percent of Chinese (data from the phonebook) is at or above the Chinese quota (87%), $(\text{percent}C_{bi} - 0.87)^k$ are k^{th} order polynomials of the Chinese proportion (estimated separately on each side of the cutoff), centered around the block quota. The coefficient of interest is β , which represents the magnitude of the discontinuity at the quota limit.

The following 2 equations use the assignment dummy from HDB data (QC_{bit}) as the key independent variable. Equation (2) only controls for smooth functions of the running variable, while equation (3) controls for other observable characteristics:

$$y_{bit} = \alpha + \beta QC_{bit} + \sum_{k=1}^4 \phi_k (\text{percent}C_{bi} - 0.87)^k \quad (2)$$

$$+ \sum_{k=1}^4 \gamma_k QC_{bit} * (\text{percent}C_{bi} - 0.87)^k + \varepsilon_{bit}$$

$$y_{bit} = \alpha + \beta QC_{bit} + \sum_{k=1}^4 \phi_k (\text{percent}C_{bi} - 0.87)^k$$

$$+ \sum_{k=1}^4 \gamma_k QC_{bit} * (\text{percent}C_{bi} - 0.87)^k + B_{bi} \delta + \tau_t + \omega_i + \varepsilon_{bit} \quad (3)$$

where y_{bit} is the outcome variable for units in block b , town i and month t ; B represents other observable characteristics of the block (age of building, proportion of type 1 units, type 2 units etc.); τ_t and ω_i are month and town fixed effects. The standard errors in (3) are clustered at the town level.

The final equation is aggregated from month-block levels to block levels only:

$$y_{bi} = \alpha + \beta \textit{percent } QC_{bi} + \sum_{k=1}^4 \phi_k \textit{percent } C_{bi}^k + B_{bi} \delta + \omega_i + \varepsilon_{bi} \quad (4)$$

where *percent* QC_{bi} is the proportion of months the Chinese quota is binding in the entire period of the sample. For this analysis, I use observations within 10% of the quota but I do not control for smooth functions of polynomials separately on the right and left of the quota because I have aggregated the quota dummies (QC_{bit}) across months (my key regressor is not a dummy anymore).

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. Moreover, 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. 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 cutoff 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 cutoff they land (Lee and Lemieux, 2010). Finally, to the extent that household location decisions are persistent (due to family ties, for example), we would expect pre-1989 communities to be very different. In my analysis, I control for the age of the apartment blocks and do not find substantially different results.

Absent the pre-policy data, the next best candidate would have been *monthly* administrative data on ethnic proportions that HDB used to determine whether the quota was binding or not. Unfortunately, HDB only reports monthly indicator variables of whether an apartment block was constrained.¹¹ Using names in annual phonebooks to proxy for monthly ethnic proportions introduce 2 sources of measurement error. First, names may not match perfectly to ethnicities. If this measurement error was classical, this should bias against estimating any discontinuities. Even if names were 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 switched from constrained to unconstrained across months or vice versa) but there are too few switchers.

¹¹This also makes it harder for households to sort precisely around the quota cutoff because they do not know how close they are to the cutoff without knowing the ethnic proportions.

Finally, there is limited data on other observables besides age and the number of rooms in a unit. HDB public housing units are relatively homogeneous. I am able to explain between 75 - 80% of the price variation using the controls I have.

5 Results

Figure 1 shows estimates of the densities of the running variables (McCrary, 2008). As shown in Figures 1a and 1c, the densities of block level Chinese and Indian proportions are not statistically significantly discontinuous at the quota cutoffs. The log difference in heights are -0.048 (0.06 s.e.) and .009 (0.08 s.e.) respectively. Figure 1b 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.). However, I find that the bunching pattern does not appear to be related to a manipulation of the treatment assignment. As discussed in Section 2.1, the Malay quotas incentivize non-Malay sellers to bunch slightly below the quota limit because Malay-constrained units owned by them tend to sell for less and if anything, Malay sellers have an incentive to bunch slightly above the quota limit. While I do not observe seller ethnicity from the HDB transactions data, I do observe the ethnicity of “exits” from the phonebook. I matched the names of each household in the 2005 and 2006 phonebook and defined “exits” as households who did appear in the HDB block in 2005 but not 2006. Contrary to expectations, I found that the proportion of Malay “exits” was 1.3% lower for Malay constrained units (the p-value is 12%).¹² 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 quota had reduced the number of Malay enclaves tremendously, they have a lower propensity to leave Malay-constrained units. Furthermore, I will argue that this pattern of bunching cannot account for all the price effects found below.

Figure 2a summarizes the effect of being in a block with 87% or more Chinese (as measured using the phonebook data) on the probability that the Chinese quota binds in a month (as measured by the monthly quota status data from the HDB website). This is an estimation of equation (1) using observations within 10% of the quota cutoff. Figures 3b and 3c measure the same effect for Malay and Indian block quotas. The figures show that there is a statistically significant positive discontinuity in the probability that the quota binds, right at the policy thresholds associated with the Chinese, Malay and Indian quotas. However, the probability that the quota binds is greater than 0 below the quota

¹²The proportion of non-Malay sellers is calculated as Chinese plus Indian “exits”, as a share of the total number of “exits” in the HDB block. I also calculated this as a share of the total number of households in the block, assuming that all households are potential sellers. The results are similar.

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 previous section. The noise introduced by the measurement error would bias against finding discontinuities unless the measurement error is correlated with the quota status, which seems unlikely. Because of this, the same regression within 2% and 5% of the quota limit does not significantly increase the probability that the quotas bind in a month. Therefore, throughout this analysis, I will only focus on using observations within 10% of the quota cutoff.

Table 4 reports results from a seemingly unrelated regression, with a system of outcome variables using equation (3). The outcome variables are *proportion type 3*, ..., *proportion type 6* units in each block using the restricted data from the census of all units in every HDB block.¹³ 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 estimates show that the supply of unit types in Chinese- and Indian-constrained blocks are significantly different from unconstrained blocks but not so for blocks close to the Malay quota. These differences for Chinese and Indian blocks persisted since before the quota was introduced in 1989 because the estimates do not appear to be very different comparing columns 1 and 5 against columns 2 and 6. Column 1 shows that Chinese-constrained blocks have more type 3, type 4 and type 5 units but fewer type 6 units (all significant at 1%). Blocks close to the Malay quota are quite similar above and below the quota. Blocks above the Indian quota have significantly more type 4 and type 5 units, but significantly fewer type 3 units. While these significant differences in observable differences are definitely a concern, it is comforting that the sign and magnitude of the coefficients are not monotonic in the type of the units. In general, a higher type is higher quality (type 3 has 2 bedrooms and type 4 has 3 bedrooms, for example) and it does not appear that Chinese-constrained units tend to have systematically more high quality units. However, there is definitely a concern that after controlling for smooth functions of observable characteristics, there could be unobservables that generate discontinuities in prices. A regression of prices just on smooth functions of the types of units (the dependent variables in the seemingly unrelated regression) has an R-squared of 0.65 indicating that 35% of the variation in prices can-

¹³There are 8 types of units. Higher types are more expensive. 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 $\ln price$ on *proportion type 3* to *proportion type 6* is 0.65 and including the other 4 types only increases the R-squared by 0.007.

not be explained by these observable characteristics. Unfortunately, I have not been able to obtain data on other observable characteristics. 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 (including controls on the number of units of each type, age, polynomials of ethnic proportions and month and town fixed effects), can explain between 75-80% of the price variation in the data.

Table 5 reports results on prices. Chinese-constrained units are 7% more expensive. The size of this discontinuity is 4%, controlling for unit types and town and month fixed effects. The size of these discontinuities represent 4 to 7 times the median monthly income of the Chinese (S\$2,335).¹⁴ Malay-constrained units are 3 to 5% cheaper and Indian-constrained units are 2 to 3% cheaper. In terms of monthly income, these discontinuities are 4 to 7 times the median monthly income of the Malays (S\$1,790) and 2 to 3 times the median monthly income of the Indians (S\$2,167). Figure 3 illustrates these results on prices. The signs of these discontinuities are robust to the inclusion of observable characteristics. The fact that bunching above the Malay quota cutoffs is associated with lower prices for Malay-constrained units is suggestive evidence that the bunching patterns are not due to self-selection of treatment status. If average prices are lower for Malay-constrained units, we should expect bunching below the thresholds not above. Although not statistically significant, the finding that the proportion of Malay “exits” was lower above the cutoff is another piece of evidence that this pattern of bunching cannot explain the price effects. If upgrades were a normal good, then, a higher proportion of non-Malay “exits” (higher income group) above the cutoff would tend to bias the price of Malay-constrained units upwards, instead of downwards.

The result on prices is interesting when compared to the results on the quality of the units sold (Table 6). I use unit types as a measure of quality, where the dependent variable is an integer between 1 and 8. A higher number indicates a better unit type. I find that Chinese-constrained units that are sold are of worse quality even though the prices are higher. This is consistent with the finding of no bunching/smooth density of Chinese proportions. If non-Chinese sellers bunched below the cutoff and Chinese sellers bunched above the cutoff, as discussed in Section 2.1, this selection effect would likely lead to higher quality units being sold right above the cutoff but this is not what I find. This suggest that there exists frictions in the market so that selles are not able to precisely control the treatment status of their unit when it is sold. Conversely, Indian-constrained units are of significantly better quality even though the prices of those units are lower. Malay-constrained units that are sold are of lower quality, consistent with the finding that the prices are also lower. Figure 4 illustrates these results on quality.

Table 7 reports results of the quota impact on the proportion of units sold. An increase

¹⁴Calculated using the average price of units sold (S\$240,000).

in the number of months that a quota binds significantly decreases the proportion of units sold for all quotas. On average, the Chinese and Malay quota bind for 2 months and the Indian quota binds for 4 months. At these averages, the proportion of units sold is lower by 2% for the Chinese, Malay and Indian quotas. On average, only 0.2% of units are sold in a month. These estimates represent an increase in the time-to-sell margin by 10 months. Table 8 summarizes the impact of the quota on all 3 dimensions, quantity, price and quality.

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 is not enough 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. I show that this pattern of bunching is unlikely due to thin markets and search frictions. Even if there were selection effects, they cannot fully account for the discontinuities I find.

Using observations within 10% of the quota cutoff, I find that units sold just above the quota limits are significantly different than units below the quota limits, along the price, quantity and quality dimensions. Chinese-constrained units are more expensive even though they are of significantly lower quality than the unconstrained units. Conversely, Indian-constrained units are cheaper but of higher quality. Malay-constrained units that were sold are cheaper and of lower quality. In addition to these effects on the price and quality margin, I also find that constrained units are harder to sell. Unfortunately, without knowing the ethnicity of the buyer and the seller nor their preferences, it is hard to make normative judgements based on the estimated discontinuities. Wong (2008) estimates these preferences using a structural model and performs welfare simulations.

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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.	Level	Description
Price	35718	246477	70798	Month-Block	Average transaction price in a block (Singapore dollars)
Percent sold	8067	4%	3%	Block	Percent of units in a block that was sold within the sample period
Chinese quota	8067	11%	29%	Month-Block	Percent of units where Chinese quota binds
Malay quota	8067	11%	28%	Month-Block	Percent of units where Chinese quota binds
Indian quota	8067	21%	35%	Month-Block	Percent of units where Chinese quota binds
Percent Chinese	8067	78%	11%	Block	Percent of Chinese in a block
Percent Malay	8067	8%	6%	Block	Percent of Malay in a block
Percent Indian	8067	14%	9%	Block	Percent of Indian in a block
Age	35718	17.64	8.54	Block	Average age of HDB blocks
Percent type 1	8067	0.05%	2%	Block	Percent of units in a block that is Type 1
Percent type 2	8067	0.96%	8%	Block	Percent of units in a block that is Type 2
Percent type 3	8067	23.28%	37%	Block	Percent of units in a block that is Type 3
Percent type 4	8067	37.64%	34%	Block	Percent of units in a block that is Type 4
Percent type 5	8067	25.10%	32%	Block	Percent of units in a block that is Type 5
Percent type 6	8067	12.89%	32%	Block	Percent of units in a block that is Type 6
Percent type 7	8067	0.01%	1%	Block	Percent of units in a block that is Type 7
Percent type 8	8067	0.08%	3%	Block	Percent of units in a block that is Type 8

Table 4
Results of seemingly unrelated regression on ethnic quotas^a

Quota	Chinese		Malay		Indian	
	Pre- and post- quota	Pre-quota only	Pre- and post- quota	Pre-quota only	Pre- and post- quota	Pre-quota only
Sample	(1)	(2)	(3)	(4)	(5)	(6)
Proportion type 3	0.01** (0.01)	-0.04*** (0.01)	0.01 (0.01)	-0.02*** (0.01)	-0.02*** (0.004)	-0.05*** (0.01)
Proportion type 4	0.01** (0.01)	0.05*** (0.01)	-0.01 (0.01)	0.02*** (0.01)	0.02*** (0.004)	0.02*** (0.01)
Proportion type 5	0.02*** (0.01)	0.03*** (0.01)	0.00 (0.004)	-0.00001 (0.01)	0.01** (0.004)	0.03*** (0.01)
Proportion type 6	-0.05*** (0.004)	-0.05*** (0.01)	0.01 (0.01)	0.002 (0.01)	0.002 (0.004)	0.01** (0.01)
Observations	87512	64610	64963	50291	140200	121500

^a The regression equation is $y_{bit} = \alpha + \beta QC_{bit} + \sum_{k=1}^4 \phi_k (\text{percent}C_{bi} - 0.87)^k + \sum_{k=1}^4 \gamma_k QC_{bit}^* (\text{percent}C_{bi} - 0.87)^k + \varepsilon_{bit}$ where y_{bit} is the outcome variables *proportion type 2, ... , proportion type 6* flats in each block b , town i and month t ; QC_{bit} is a dummy whether the (C)hinese quotas are binding; $(\text{percent}C_{bi} - 0.87)^k$ are k^{th} order polynomials of the percent Chinese, centered around the block quota. I repeat the exercise for the Malay (whose block quota equals 0.25) and for the Indians (whose block quota equals 0.13). 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 the blocks that were built before the policy started in 1989. Standard errors are in parentheses. ***Statistically significant at 1%. **Statistically significant at 5%. *Statistically significant at 10%.

Table 5
Results of the quota impact on price^a

Quota	Chinese		Malay		Indian	
	ln price	ln price	ln price	ln price	ln price	ln price
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Quota dummy	0.07*** (0.01)	0.04*** (0.01)	-0.05*** (0.01)	-0.03*** (0.00)	-0.02** (0.01)	-0.03** (0.01)
Ethnic proportion	-0.49*** (0.16)	-0.09 (0.12)	0.02 (0.18)	-0.19* (0.10)	-1.87*** (0.17)	-0.37** (0.15)
(Ethnic proportion) ²	9.00*** (3.47)	-0.25 (0.28)	-9.20*** (3.50)	0.09 (0.18)	-24.31*** (3.00)	0.27 (0.17)
(Ethnic proportion) ³	198.32*** (32.68)	-1.59 (2.40)	-17.10 (32.60)	-5.20** (2.36)	163.33*** (33.92)	-2.69 (1.92)
(Ethnic proportion) ⁴	354.87 (467.81)	11.08* (5.49)	858.17* (447.36)	7.15 (6.99)	2993.26*** (428.39)	2.58 (3.63)
Quota x Ethnic proportion	-0.60* (0.32)	6.05 (25.72)	0.59** (0.28)	-7.53 (17.27)	1.20*** (0.25)	44.17* (23.01)
Quota x (Ethnic proportion) ²	25.40*** (8.50)	54.11* (28.80)	6.47 (6.82)	-3.13 (18.96)	15.26*** (5.82)	-15.35 (26.58)
Quota x (Ethnic proportion) ³	-211.53*** (64.11)	213.61 (327.28)	-16.50 (51.24)	500.67 (296.45)	-43.37 (48.07)	294.73 (229.23)
Quota x (Ethnic proportion) ⁴	-3971.24*** (1150.87)	-816.81 (604.56)	512.29 (868.09)	-548.76 (848.86)	-1865.46** (769.96)	-294.25 (486.67)
Block level controls	No	Yes	No	Yes	No	Yes
Town fixed effects	No	Yes	No	Yes	No	Yes
Month fixed effects	No	Yes	No	Yes	No	Yes
Observations	19314	19314	14862	14862	32114	32114
R-squared	0.02	0.80	0.01	0.75	0.01	0.78

^a The regression equation is $\ln Price_{bit} = \alpha + \beta QC_{bit} + \sum_{k=1}^4 \phi_k (\text{percent}C_{bi} - 0.87)^k + \sum_{k=1}^4 \gamma_k QC_{bit}^* (\text{percent}C_{bi} - 0.87)^k + \varepsilon_{bit}$ where $\ln Price_{bit}$ is the log of the price of units in block b , town i and month t ; QC_{bit} is a dummy that is 1 when the Chinese (C) quotas are binding; $(\text{percent}C_{bi} - 0.87)^k$ are k^{th} order polynomials of the percent Chinese, centered around the block quota. The controls are other observable characteristics of the block, (age of building, proportiona of type 1 flats, type 2 flats, etc.), month and town fixed effects. I repeat the exercise for the Malay (whose block quota equals 0.25) and for the Indians (whose block quota equals 0.13). Standard errors clustered at the town level are in parentheses. ***Statistically significant at 1%. **Statistically significant at 5%. *Statistically significant at 10%.

Table 6
Results of the quota impact on quality of units sold^a

Quota	Chinese	Malay	Indian
Dependent variable	Flat Type Sold	Flat Type Sold	Flat Type Sold
	(1)	(2)	(3)
Quota dummy	-0.05* (0.03)	-0.08*** (0.03)	0.04* (0.02)
Ethnic proportion	-2.51*** (0.48)	0.83 (0.60)	-4.42*** (0.52)
(Ethnic proportion) ²	33.77*** (10.41)	1.51 (11.61)	-63.29*** (9.30)
(Ethnic proportion) ³	653.33*** (98.02)	-106.64 (108.25)	461.34*** (105.28)
(Ethnic proportion) ⁴	1273.14 (1403.38)	-199.71 (1485.44)	8818.55*** (1329.68)
Quota x Ethnic proportion	0.92 (0.97)	2.61*** (0.92)	4.10*** (0.77)
Quota x (Ethnic proportion) ²	26.72 (25.49)	15.85 (22.66)	60.28*** (18.06)
Quota x (Ethnic proportion) ³	-970.03*** (192.34)	-244.69 (170.13)	-331.34** (149.21)
Quota x (Ethnic proportion) ⁴	-9300.65*** (3452.52)	975.02 (2882.48)	-7780.61*** (2389.90)
Observations	19314	14862	32114
R-squared	0.01	0.003	0.004

^a The regression equation is $Flat\ Type\ Sold_{bit} = \alpha + \beta QC_{bit} + \sum_{k=1}^4 \phi_k (percentC_{bi} - 0.87)^k + \sum_{k=1}^4 \gamma_k QC_{bit}^* (percentC_{bi} - 0.87)^k + \varepsilon_{bit}$ where $Flat\ Type\ Sold_{bit}$ is the type of flat units sold, denoted by an integer between 1 and 8 (there are 8 flat types), in block b , town i and month t . A higher number indicates a better flat type; QC_{bit} is a dummy that is 1 when the Chinese (C) quotas are binding; $(percentC_{bi} - 0.87)^k$ are k^{th} order polynomials of the percent Chinese, centered around the block quota. I repeat the exercise for the Malay (whose block quota equals 0.25) and for the Indians (whose block quota equals 0.13). Standard errors clustered at the town level are in parentheses. ***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

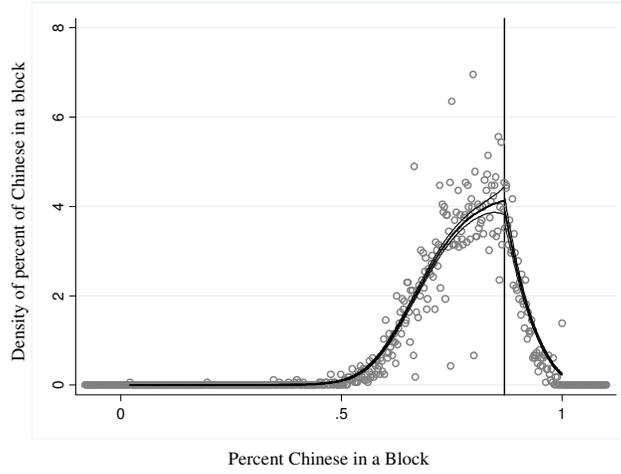
Quota	Chinese	Malay	Indian
Dependent variable	Proportion Sold	Proportion Sold	Proportion Sold
Proportion of months the quota is binding	-0.01*** (0.002)	-0.01*** (0.001)	-0.004* (0.002)
Ethnic proportion	-3.91 (6.47)	-5.01 (4.79)	0.35 (0.39)
(Ethnic proportion) ²	3.31 (5.65)	33.96 (32.28)	-3.05 (5.86)
(Ethnic proportion) ³	dropped	-98.68 (94.51)	9.22 (35.99)
(Ethnic proportion) ⁴	-0.71 (1.27)	104.93 (101.60)	2.87 (76.79)
Block level controls	Yes	Yes	Yes
Town fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Observations	3948	2896	6322
R-squared	0.10	0.12	0.11

^a The regression equation is $pSold_{bi} = \alpha + \beta percentQC_{bi} + \sum_{k=1}^4 \varphi_k percentC_{bi}^k + B_{bi} \delta + \tau_{bi} + \omega_{bi} + \varepsilon_{bi}$ where $pSold_{bi}$ is the proportion of units sold in block b , town i , aggregated across months; $percentQC_{bi}$ is the proportion of months the Chinese (C) quota is binding; g ; $percentC_{bi}^k$ are k^{th} order polynomials of the percent Chinese; B_{bi} represents other observable characteristics of the block, (age of building, proportion of type 1 flats, type 2 flats, etc.); τ_{bi} and ω_{bi} are month and town fixed effects. For this analysis, I use observations within 10% of the quota but I do not control for smooth functions of polynomials separately on the right and left of the quota. I repeat the exercise for the Malay and for the Indians. Standard errors clustered at the town level are in parentheses. ***Statistically significant at 1%. **Statistically significant at 5%. *Statistically significant at 10%.

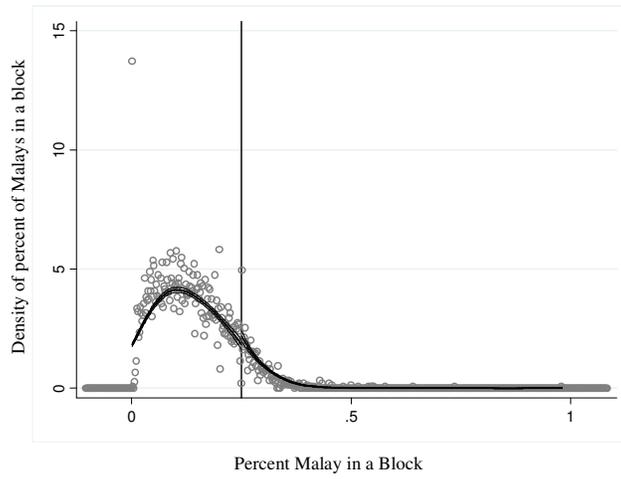
Table 8
Summary of the impact of the quota on quantity, price and quality

	Chinese Quota	Malay Quota	Indian Quota
Quantity	Lower	Lower	Lower
Price	Higher	Lower	Lower
Quality	Lower	Lower	Higher

a. Density of percent of Chinese in a block



b. Density of percent of Malays in a block



c. Density of percent of Indians in a block

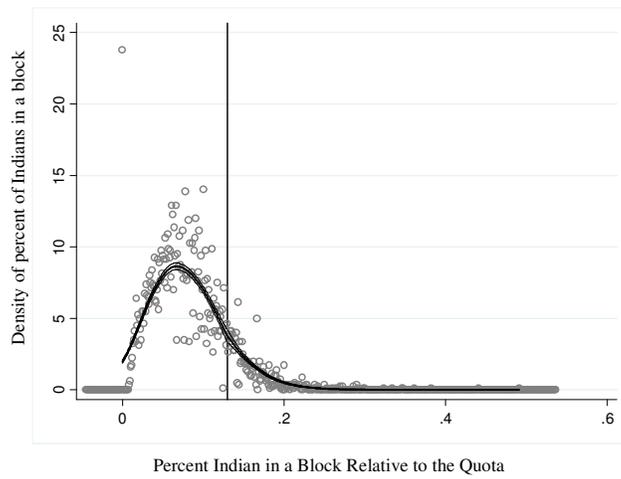
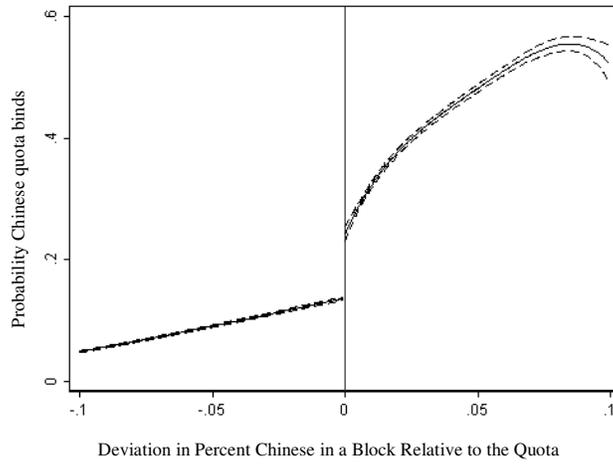
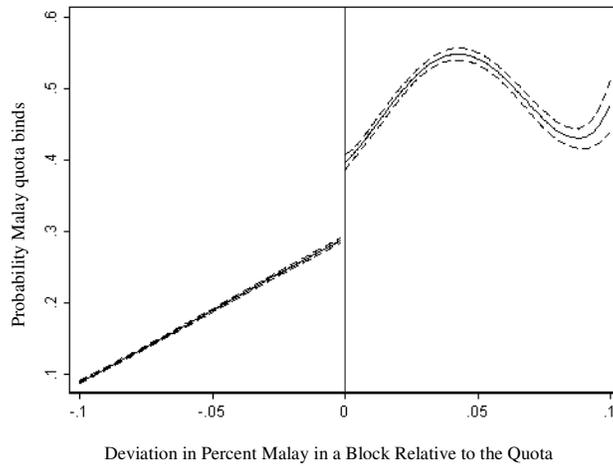


Fig. 1. Testing for discontinuities in the density of the running variable (ethnic proportions). The vertical lines correspond to the quota cutoffs.

a. Probability that the Chinese Quota Binds, 10% Above and Below the Quota



b. Probability that the Malay Quota Binds, 10% Above and Below the Quota



c. Probability that the Indian Quota Binds, 10% Above and Below the Quota

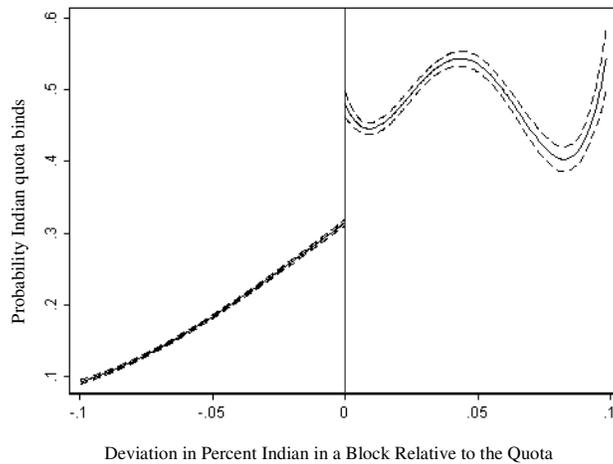
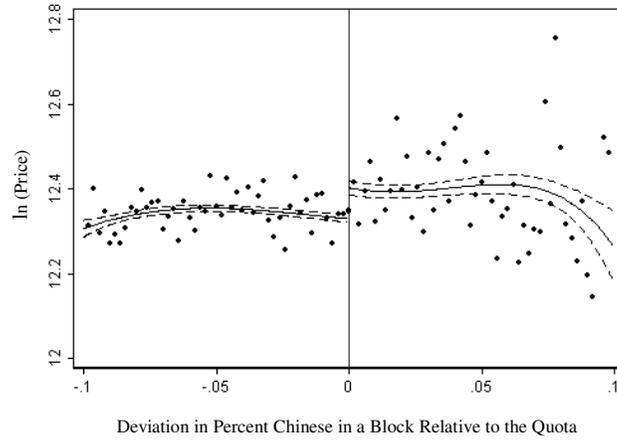
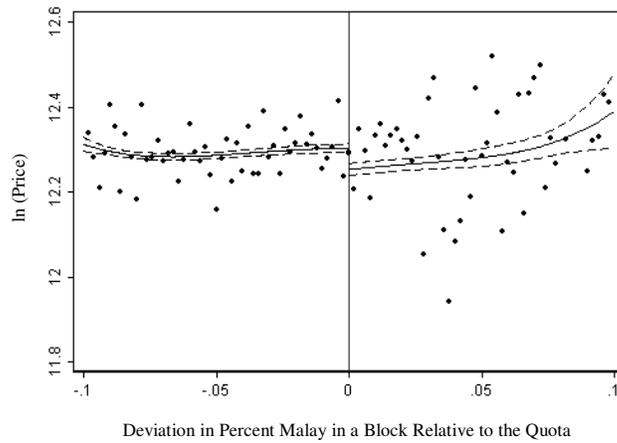


Fig. 2. Testing for discontinuity in the probability that the quota binds, 10% above and below the quota. Each panel in this figure is constructed using the following procedure for observations within 10% of the ethnic quotas: (i) regress Q (a dummy for whether the quota is binding) on smooth functions of the corresponding running variable (4th order polynomials), separately, once to the left and once to the right of the quota; (ii) plot the predicted probabilities above and below the quota separately. Repeat the exercise for the Malay quotas and Indian quotas. The dashed lines represent 95% confidence intervals.

a. The Impact of Chinese Block Quotas on $\ln(\text{price})$



b. The Impact of Malay Block Quotas on $\ln(\text{price})$



c. The Impact of Indian Block Quotas on $\ln(\text{price})$

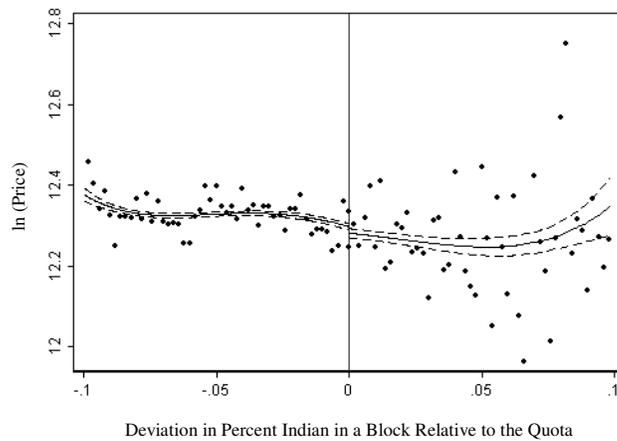
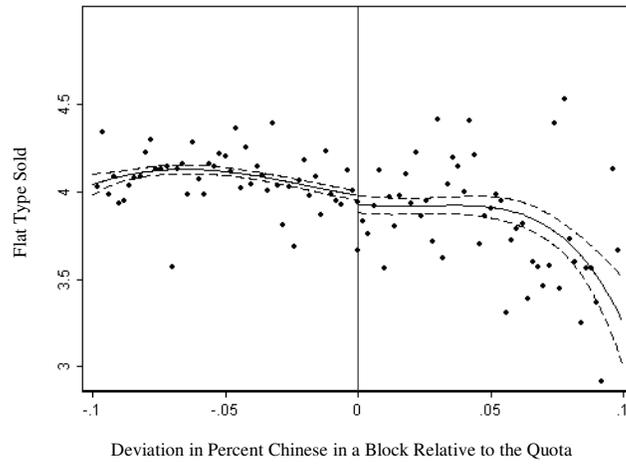
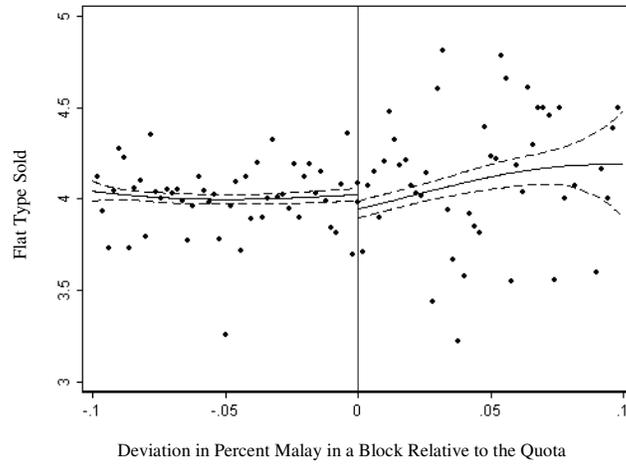


Fig. 3. Impact of block quotas on $\ln(\text{Price})$, 10% above and below the quota. Each panel in this figure is constructed using the following procedure for observations within 10% of the ethnic quotas: (i) regress the log of transaction prices on smooth functions of ethnic proportions (two 4th order polynomials, above and below the quota) and a dummy that is one when the corresponding block quota is binding; (ii) plot the predicted prices above and below the quota separately (solid line) as well as the 95% confidence interval (dashed lines); (iii) plot means of $\ln(\text{price})$ for each 1% bin. I repeat the exercise for the Malay quotas and Indian quotas.

a. The Impact of Chinese Block Quota on Type of Flat Sold, 10% Above and Below the Quota



b. The Impact of Malay Block Quota on Type of Flat Sold, 10% Above and Below the Quota



c. The Impact of Indian Block Quota on Type of Flat Sold, 10% Above and Below the Quota

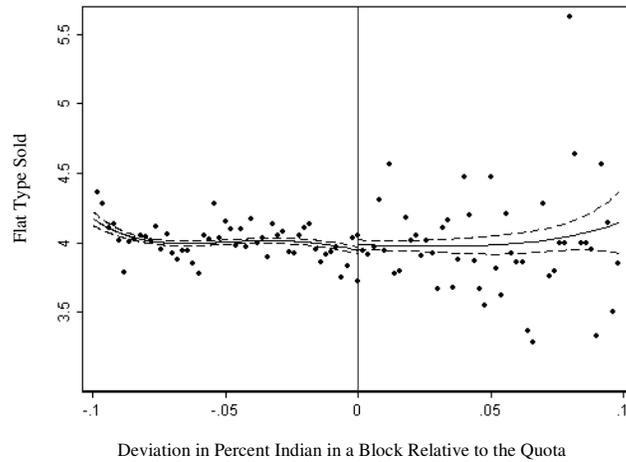


Fig. 4. The impact on type of flat sold, 10% above and below the quota. The dependent variable is an integer between 1 and 8, describing the type of flat sold. A higher flat type is better. Each panel in this figure is constructed using the following procedure for observations within 10% of the ethnic quotas : (i) regress *Flat Type Sold* on smooth functions of the corresponding running variable (two separate 4th order polynomials, one to the left and one to the right of the quota) and a dummy that is one when the corresponding block quota is binding; (ii) plot the predicted *Flat Type Sold* above and below the quota separately (iii) plot means of for each 0.2% bin. Repeat the exercise for the Malay quotas and Indian quotas. The dashed lines represent 95% confidence intervals.