Data Appendix

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

1 Sample selection procedure

Ethnic proportions from phonebook

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. I use the postal sector together with the fourth digit of the postal code to identify 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 further dropped 204,248 phone listings because the street address did not appear on the Ethnic Integration Policy website (there is no quota data for these addresses, mostly because they are private housing units. During my sample period, less than 20% of residents in Singapore live in private housing). 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 (as discussed in Section 2). The final sample includes 548,024 listings.

HDB blocks

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.

2 Evidence of demand-side choice restrictions and segregation preferences (E1 in the theory)

In the theory, I explained in E4 that the differences in average prices between constrained and unconstrained blocks is a combination of *negative* price differences due to segregation preferences (E1) and *positive* price differences due to thin markets (E3). In particular, the effect due to E1, *increases* with the share of transactions that involve non-segregated buyers ($s^2_{88} + s^3_{88}$ in equation (2) in Section 4).

To this this, we could augment the treatment effect specification (equation (3) in the paper) by interacting the key regressor, whether the quota is binding for block b in month t, with the transaction shares involving non-segregated buyers (and also controlling separately for the transaction shares). Then, E1 predicts the coefficients on the interaction terms should be negative. Unfortunately, I cannot identify the ethnicity of the buyers using the transactions data.

Proxy for buyer ethnicity

To address this data limitation, I use the fact that buyers who bought during my sample period have to change their phonebook address after moving to the new unit. Therefore, I can use the ethnicity of the movers who changed their phonebook address between 2005 and 2006 as a proxy for the ethnicity of buyers.

To identify movers, I match the names and postal codes of all HDB residents in my sample in the 2005 phonebook with the names and postal codes in the 2006 phonebook (postal codes identify unique HDB blocks).[1] I define stayers as households living in the same postal codes in 2005 and 2006. Movers are households who changed their postal code from 2005 to 2006. Entrants are phonebook listings that only appeared in the 2006 phonebook only. I was able to identify 524,541 stayers, 20,646 movers and 39,299 entrants. I had to drop 74 movers because I could not identify their ethnicities.

I use the ethnicity of movers moving in to proxy for the ethnicity of buyers. Importantly, I do not have apartment unit numbers, so I cannot identify moves *within* a block. This also means I cannot match a mover moving out of a unit within a block to a mover moving in because more than 70% of the blocks have multiple movers moving in. I also cannot match the ethnicity of movers to individual transactions because most blocks have multiple movers and multiple transactions.

While I do not have ethnic buyer dummies for individual buyers, we can think of implementing an aggregated version of the regression above using ethnic *shares* of movers instead of ethnic dummies. For example, I use the data from the phonebooks to calculate the Malay mover share as $\frac{\text{Number of movers moving into neighborhood } j \text{ who are Malay}}{\text{Number of movers moving into neighborhood } j}$. I aggregate to the HDB neighborhood level because HDB blocks have too few movers (the ethnic shares at the block level are too noisy). For example, with only two movers, ethnic mover shares would either be 0%, 50% or 100%.

Phonebooks are published every April 1st. So, comparing 2005 and 2006 phonebooks would cover most households who changed phone listings between April 1st, 2005 and March 31st, 2006. To match the transactions data with these publication dates, I had to drop 10,666 transactions outside of this window. Additionally, I dropped 63 more transactions because they belonged to HDB neighborhoods with fewer than 10 movers (again, the ethnic shares would be too noisy).

Test for demand-side choice restrictions and segregation preferences

To implement the test above, instead of using transaction shares of non-segregated groups, I use dummies of high versus low shares of non-segregated movers so that the coefficients on the interaction terms can be easily interpreted as differences in prices (in logs). That is, I interact the quota dummies with dummies for whether the ethnic shares for the non-segregated groups at the HDB neighborhood level are above the median

[1] About 8.5% of the data had instances of households sharing the same name residing in the same postal code. Since names are used to define ethnicities, listings with the same names also have the same ethnicities. So, I did not have to worry about the ethnicity, but I had to determine which of the duplicate names were stayers, movers and entrants. As an example, suppose there were two listings (both with the name John Doe) living in postal code 123123 in 2005. In 2006, there were three listings (all with the name John Doe) living in three different HDB postal codes and they appear in the phonebook in the following order: John Doe-123123, John Doe-456456 and John Doe-789789 respectively. There is one stayer in postal code 123123 (there is the possibility that both John Doe's living in 123123 moved to postal codes 456456 and 789789 in 2006 and the John Doe in 123123 in 2006 is an entrant, but I assume that a John Doe moving out and another John Doe moving in is unlikely compared to the possibility that one of the John Doe's was a stayer). Now that I have defined one of the two John Doe's in 123123 in 2005 as a stayer, I need to know which of the John Doe's in 456456 or 789789 is the mover and which is the entrant. To do this, I assume that the order in the phonebook is preserved across years. Each phone listing includes an id (essentially a unique number affiliated with each phone listing). If there were multiple John Doe's living in the same postal code in 2005 and 2006, I assume that the order of the names (and the order of their id's) is preserved in 2005 and 2006. I checked this assumption by looking at stayers. There were 153,450 cases of stayers sharing the same name and postal code. I compared the id of these stayers in 2005 and 2006 and checked that the order of their id's are preserved from 2005 to 2006. I sorted these phone listings in increasing order using their id's in 2005, then checked that the id's in 2006 are also in increasing order for a large majority of the cases (this is true for all but 29 listings). Back to the example, since an entrant is a new listing, it would be added after the first two listings. So, John Doe in 456456 is the mover who moved from 123123 and John Doe in 789789 is the new listing (the entrant). This is how I classified stayers, movers and entrants for the 8.5% of data with multiple names in the same postal codes.

ethnic shares.[2] For the Chinese quota, for example, I interact the Chinese quota dummy with two dummies that are: (1) one if neighborhood j has a Malay mover share that is at least as high as the median Malay mover share across all neighborhoods; (2) one if neighborhood j has an Indian mover share that is at least as high as the median Indian mover share across all neighborhoods. This analysis compares constrained blocks in neighborhoods with high versus low shares of non-segregated movers. Demand-side choice restrictions and segregation preferences should lead to *lower* prices for constrained blocks with *more* non-segregated movers moving in (E1). That is, the coefficients on the interaction terms should be negative.

Table A3 augments equation (3) to include the interaction terms and the dummies for high shares of non-segregated buyers, as described above. Column 1 shows that amongst Chinese-constrained blocks, those that are in neighborhoods with a high share of Malay movers have prices that are 12.3% lower (consistent with E1, Malay buyers have lower WTP than Chinese buyers). But, I do not see this effect for the interaction with Indian movers (it is actually positive). This suggests that Malay and Chinese buyers have different WTP, but not Indian versus Chinese buyers. Column 2 is also consistent with E1. Malay-constrained blocks have prices that are 5.68% lower in neighborhoods with a high share of Chinese movers moving in. The coefficient for the interaction with Indian mover shares is insignificant. Column 3 shows that Indian-constrained blocks have *lower* prices in neighborhoods with a high share of Malay movers. The coefficient for the interaction for Chinese mover shares is positive.

In summary, I find evidence of E1, especially amongst Malay versus Chinese movers for Chinese-constrained blocks and Malay-constrained blocks and amongst Malay versus Indian movers for Indian-constrained blocks. Unfortunately, I do not have much variation in ethnic mover shares at the neighborhood level, so that these results are not robust to adding more controls. They are robust to adding month fixed effects, but not to adding town fixed effects and block controls as those in column (3) in Table 4. Standard errors are clustered at the block level. The interaction terms are significant for the Chinese quotas if standard errors are clustered at the neighborhood level, but they are not significant for the Malay and Indian quotas.

Data issues

There are some issues when using ethnic mover shares to proxy for the ethnicity of buyers.

1. I did not use the location choice of entrants because the large number of entrants relative to the number of resale transactions suggest that many entrants may not be resale buyers and I have no way to determine which entrant is a buyer. Most probably, these entrants' listings were not identified in the 2005 phonebook because they changed the spelling of their names. The correlation between the number of movers who moved to an HDB neighborhood and the number of entrants in a neighborhood is 0.93 and the correlation between the number of movers in a neighborhood and the number of resale transactions is 0.88. These high correlations suggest that neighborhoods that attract more movers also tend to be neighborhoods that attract more entrants and buyers.

2. Since I cannot match movers moving out with movers moving in, I am not able to differentiate the 4 types of transactions in the theory (these 4 types are defined using buyer *and* seller ethnicity). For example, for each HDB neighborhood, I know the share of movers moving in who are Chinese, but I cannot decompose this share into whether they moved into units previously owned by Chinese, Malay or Indian.

3. There is some time difference between the month of the resale transaction and the month the phonebook listing was updated. Phonebooks are published every April 1st. So, comparing 2005 and 2006 phonebooks would cover most households who changed phone listings between April 1st, 2005 and March 31st, 2006. Households have to update their contact information within a month of moving. So, this comparison may include households who moved less than a month *before* April 1st, 2005 and only updated their phone listing after April 1st, 2005. It may also exclude some households who moved in March, 2006 but did not update their phone listings until *after* March 31st, 2006. These misalignments between transactions and updates of phonebook listings will lead to differences in the number of moves and the number of resale transactions (my next point).

4. There are several reasons why movers may not be buyers. My analysis assumes that this measurement error is not correlated with the quota dummy. Consider the two cases of measurement error:

[2] I also control separately for dummies for neighborhoods with high non-segregated mover shares.

(a) Some movers are erroneously counted as buyers (overcounting buyers): Some movers are renters (but this is only 2% of the HDB market), some movers inherited their new unit (this is also likely to be a small share), some movers who moved early in the sample period bought their units before the sample period. These are instances of movers identified using the phonebooks who are not buyers in my sample period.

(b) Some buyers are not counted as movers (undercounting buyers): Some buyers did not change their listing in the phonebook in my sample period (they chose not to list, or they had to renovate, so they bought the house in the sample period but moved after the sample period), or some buyers moved within the same HDB block, or some buyers were entrants. These are instances of buyers in my sample period not being represented by movers.

3 Evidence of supply-side choice restrictions and thin markets (E3 in the theory)

As discussed in Section 6.1, on average, prices are higher for Chinese-constrained blocks, consistent with E3. As explained in E3 in the theory, Chinese buyers who cannot buy from non-Chinese sellers in the 88% blocks are facing a supply-side constraint (they cannot buy 12% of the units in the 88% block). If markets are thick, this restriction should not have price effects because substitutes are available for the Chinese buyers. If markets are thin, this supply-side choice restriction could lead to higher prices. This suggests that the price effect should be *weaker* if more substitutes are available.

Proxy for availability of substitutes

To proxy for the amount of substitutes available in a housing market, I use the log of the total number of units in the housing stock in town k (I calculate this using the HDB census of housing units). The idea is that towns with larger housing stocks are thicker. There are 26 towns.

Test for supply-side choice restrictions and availability of substitutes

To implement the test above, I interact the quota dummies with the log of the (de-meaned) housing stock in town k, and also control for this separately. This analysis compares constrained blocks in towns with above average versus below average housing stocks, as proxies for thicker versus thinner markets. Supply-side choice restrictions should lead to *higher* prices in towns with fewer substitutes available (E3). That is, the coefficients on the interaction terms should be negative (larger housing stocks mean more substitutes are available).

Table A4 repeats my preferred specification for price effects (column 3 of Table 4), but drops town fixed effects (because housing stocks are calculated at the town level). I find evidence of supply-side choice restrictions (E3) for Chinese quotas but not Malay and Indian quotas. Column 1 shows that amongst Chinese-constrained blocks, those that are in towns with larger housing stocks indeed have *lower* prices. But, the coefficient on the interaction terms are not significant for Malay and Indian quotas (columns 2 and 3).

4 Summarize effects on transaction values

To quantify the differences in transaction values between constrained and unconstrained blocks, I use the treatment effect estimates on prices and quantities to calculate the effect on transaction values (price times quantity). Table A5 summarizes my calculations. I have numbered each column from 1 to 9. For each of the three quotas (Chinese, Malay and Indian), I have numbered the three rows from a to c. This facilitates the identification of cells within each of the three quotas. For example, cell 5a corresponds to the differences in transaction values between unconstrained and constrained blocks for all three quotas (1434 for Chinese quotas, 3200 for Malay quotas and 2048 for Indian quotas).

Column 1 shows that there are more HDB units in constrained blocks than in unconstrained blocks. Consequently, column 2 shows that mechanically, fewer units are sold in constrained blocks. To abstract away from this, I normalize the quantity effects by looking at effects on the *proportion of units in a block that* *are sold* (that is, I normalize the quantity effect by the total number of HDB units in a block). Therefore, the total effect on values (price times quantity) is calculated by multiplying the effect on proportion of units sold by the effect on prices. These effects should be interpreted for constrained versus unconstrained blocks, normalized by the number of units in the blocks.

Column 3 shows that the proportion of units sold for the constrained blocks is calculated by taking the proportion of units sold for the unconstrained blocks (the counterfactual) and subtracting it by the treatment effect estimated in Table 6 (I use the my preferred estimates in Panel B, columns 2, 5 and 8). For example, I estimate that the proportion of units sold for Chinese-constrained blocks is 3.85%, calculated as 4.64% (the proportion for Chinese-unconstrained blocks) minus 0.79% (the treatment effect when we increase the regressor from 0 to 1). This calculation adjusts for observable compositional differences between constrained and unconstrained blocks using controls listed in Equation (5).

Column 4 shows that the average price for the Chinese-constrained blocks is \$252,022, calculated by multiplying the price for the unconstrained blocks (\$239,975) with the treatment effect on *lnprice* (5.02% in column 3 in Table 4). Column 5 calculates the transaction values by multiplying columns 3 and 4. Finally, column 6 shows that, on average, the transaction value for Chinese-constrained blocks (\$9710) is 13% lower than the transaction value for Chinese-unconstrained blocks (\$11,144). The calculations for Malay and Indian quotas show that transaction values are 27% and 18% lower for constrained blocks, respectively.

Columns 7 to 9 further decompose the effect on transaction values into price versus quantity domains using the approximation that $d(PQ) \sim dP * Q_{counterfactual} + dQ * P_{counterfactual}$. For Malay quotas, the first difference is calculated by multiplying the price difference, holding fixed proportion of sold units at the counterfactual values (ie. $-323 = 5.31\% * (219,577 - 225,670)$). The second difference is calculated by multiplying the differences on the proportion of sold units, holding fixed prices at the counterfactual values (ie. $-2956 = 225,670 * (4\% - 5.31\%)$). Column 9 shows that the sum of these two differences (\$3280, due to rounding errors) is close to the difference reported in cell 5c (\$3200). Using this decomposition, I calculate that for the total change in transaction values, 90% is due to the quantity domain (column 8) and 10% is due to the price domain (column 7). For Indian quotas, 81% is due to the quantity domain and 19% is due to the price domain. This decomposition is not applicable for Chinese quotas because these two differences in the approximation have opposite signs.

5 Dissimilarity indices

In Section 6.3, I use dissimilarity indices to benchmark how clustered constrained blocks and neighborhoods are. The idea is to count constrained versus unconstrained blocks or neighborhoods within a town in each month in my data.

Figure 1 shows a map of HDB blocks and HDB neighborhoods. I discuss this map in p.8 in the paper. HDB neighborhoods are clusters of HDB blocks. The quota status is determined every month by HDB using ethnic proportions at the block level and at the neighborhood level. For example, for Chinese quotas, in each month, the quota status for block b in neighborhood j is defined as $max\{1(percentC_{bj} > 87\%), 1(percentC_j > 84\%)\}$ where $percentC_{bj}$ and $percentC_j$ are the Chinese proportions at the block and neighborhood level respectively. As long as one of the two quota limits are violated, the ethnic-based restrictions are imposed on transactions for that block. If the neighborhood is constrained, then, all blocks in that neighborhood are constrained (non-Chinese owners of public housing in every block in that neighborhood cannot sell to Chinese buyers).

First, I use the quota data downloaded from the HDB website to determine which blocks are constrained because of the block quota limit and which are binding because of the neighborhood quota limit.[3] That is, for each month and each of the three ethnic groups, I use the monthly ethnic quota indicators published by HDB to divide blocks into one of three mutually exclusive categories: unconstrained, block constrained (the ethnic proportion of the block is above the block quota limit) or neighborhood constrained (the block belongs to a neighborhood whose ethnic proportion is above the neighborhood quota limit). Since the dissimilarity index

[3]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 are constrained, then, I know it is because the neighborhood quota limit is binding.

is defined using binary attributes and there are three mutually exclusive categories, I calculate dissimilarity indices using block and neighborhood quota indicators separately.[4]

To calculate the dissimilarity index for neighborhood quotas, I aggregate the block-month level quota data from HDB to the neighborhood-month level, and count the number of neighborhoods that are constrained due to the neighborhood quota limit, and average across months. That is, for each month t, I calculate the dissimilarity index for neighborhood quotas for month t, $DisN_t$, and average across months:[5]

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

Likewise, to calculate the dissimilarity index for block quotas, I calculate the dissimilarity index for block quotas for month t, $DisB_t$, and average across months:

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

6 Sorting into private housing nearby

In Section 6.3, I discussed the possibility of households sorting out of public housing markets into private housing. To proxy for this margin of selection, I again appeal to the phonebook addresses. Recall that each listing in the phonebook includes the street address, postal code and the name. There is also an indicator that determines whether an address is an HDB address. To count the number of households living in private housing, I count the number of phone listings that does not have an HDB address. To proxy for private housing *near* public housing, I use the first two digits of the postal code (the postal sector). The post office sorts mail (for public and private housing units) into 79 postal sectors to ease the distribution of mail. I use these postal sectors to proxy for a market. This is admittedly not as appealing as towns, but I do not have a systematic way of assigning street addresses of private housing units to HDB towns.

To control for the ease of sorting into private housing, I calculate the share of phone listings in a postal sector that has a private housing address. Table A5 replicates my preferred specification for price effects (column 3 of Table 4) but controls for the share of private housing in the postal sector. The estimates are similar to those in column 3, Table 4.

[4]In other words, there are two quota indicators: the *block quota indicator* is 1 for blocks that are only block-constrained and 0 otherwise (the neighborhood ethnic proportions are below the neighborhood quota limits); the *neighborhood quota indicator* is 1 for blocks belonging to neighborhoods that are neighborhood-constrained and 0 otherwise.

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

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 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 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%.

Table A3. Results of demand-side choice restrictions and segregation preferences[a]

Quota	Chinese	Malay	Indian
Dependent variable	lnPrice	lnPrice	lnPrice
	(1)	(2)	(3)
Chinese Quota dummy	0.0449*		
	(0.0253)		
Chinese Quota dummy*High Malay share	-0.1358***		
	(0.0335)		
Chinese Quota dummy*High Indian share	0.1458***		
	(0.0316)		
Malay Quota dummy		-0.0372	
		(0.0242)	
Malay Quota dummy*High Chinese share		-0.0465*	
		(0.0253)	
Malay Quota dummy*High Indian share		0.0045	
		(0.0251)	
Indian Quota dummy			-0.0224
			(0.0258)
Indian Quota dummy*High Chinese share			0.0856***
			(0.0261)
Indian Quota dummy*High Malay share			-0.0642**
			(0.0263)
N	13605	10576	22563
R-squared	0.0228	0.0399	0.0177
Ethnic proportions	Y	Y	Y
Controls	N	N	N
Town	N	N	N
Neighborhood	N	N	N

[a] This analysis repeats column 1 in Table 4, but adds interactions of the quota dummies with dummies for neighborhoods with above median shares of non-segregated movers moving in (controlling separately for these dummies also). 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 A4. Results of supply-side choice restrictions and thin markets[a]

Quota	Chinese	Malay	Indian
Dependent variable	lnPrice	lnPrice	lnPrice
	(1)	(2)	(3)
Quota dummy	0.1710***	-0.0342	-0.0702
	(0.0548)	(0.0525)	(0.0532)
Quota dummy*ln(housing stock)	-0.0269**	0.0008	0.0066
	(0.0126)	(0.0156)	(0.0123)
ln(housing stock)	0.002	0.0012	-0.002
	(0.0085)	(0.0070)	(0.0069)
N	7816	5025	12273
R-squared	0.5996	0.584	0.5677
Ethnic proportions	Y	Y	Y
Controls	Y	Y	Y
Month	Y	Y	Y
Town	N	N	N
Neighborhood	N	N	N

[a] This analysis repeats column 3 in Table 4, but adds interactions of the quota dummies with the log of the (de-meaned) housing stock in a town (controlling separately for the housing stock size also). This specification drops town fixed effects. 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 town level. ***Statistically significant at 1%. **Statistically significant at 5%. *Statistically significant at 10%.

Table A5. Quantifying effects on transaction values[a]

		Stock	Units Sold	Proportion sold	Average price	Values	Share	QdP	PdQ	d(PQ)
		[1]	[2]	[3]	[4]	[5]=[3]*[4]	[6]=[5c]/[5a]	[7]=[3a]*[4c]	[8]=[4a]*[3c]	[9]=[7]+[8]
Chinese unconstrained	[a]	350,822	16,292	4.64%	\$ 239,975	\$ 11,144				
Chinese constrained	[b]	78,513	3,241	3.85%	\$ 252,022	\$ 9,710				
Difference	[c]	272,309	13,051	0.79%	\$ (12,047)	\$ (1,434)	-13%	\$ 559	\$ (1,898)	\$ (1,339)
Malay unconstrained	[a]	216,586	11,495	5.31%	\$ 225,670	\$ 11,977				
Malay constrained	[b]	79,368	3,426	4.00%	\$ 219,577	\$ 8,777				
Difference	[c]	137,218	8,069	1.31%	\$ 6,093	\$ (3,200)	-27%	\$ (323)	\$ (2,956)	\$ (3,280)
Indian unconstrained	[a]	516,123	25,341	4.91%	\$ 234,966	\$ 11,537				
Indian constrained	[b]	153,829	6,806	4.18%	\$ 226,954	\$ 9,489				
Difference	[c]	362,294	18,535	0.73%	\$ 8,012	\$ (2,048)	-18%	\$ (393)	\$ (1,713)	\$ (2,106)

[a] This table estimates how transaction values would differ for constrained blocks, using the treatment effect estimates in Tables 4 and 6. Column 3 reports counterfactual values for proportion of units sold (cell [3b]), by subtracting the treatment effect estimates in columns 2, 5 and 8 in Panel B from the proportion of units sold for unconstrained blocks (cell [3a]). Column 4 reports counterfactual values for prices of constrained blocks (cell [4b]) by multiplying average prices for unconstrained blocks (cell [4a]) by the treatment effect estimates on log prices reported in column 3 of Table 4. Column 5 reports counterfactual estimates for transaction values for constrained and unconstrained blocks normalized to have the same number of units. Column 6 calculates how much lower transaction values in constrained blocks are relative to transaction values of unconstrained blocks. Columns 7 to 9 decompose the differences in transaction values to differences due to prices versus proportions of unit sold.

Table A6. Results of controlling for share of nearby private housing[a]

Quota	Chinese	Malay	Indian
Dependent variable	lnPrice	lnPrice	lnPrice
	(1)	(2)	(3)
Quota dummy	0.0495***	-0.0255***	-0.0324***
	(0.0081)	(0.0072)	(0.0109)
Share of private housing in a sector	0.0244	0.2175***	0.1051
	(0.0936)	(0.0536)	(0.0827)
N	19533	14921	32147
R-squared	0.7978	0.7499	0.7761
Ethnic proportions	Y	Y	Y
Controls	Y	Y	Y
Month	Y	Y	Y
Town	Y	Y	Y
Neighborhood	N	N	N

[a] This analysis repeats column 3 in Table 4, but controls for the share of private housing in a postal sector. 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 town level. ***Statistically significant at 1%. **Statistically significant at 5%. *Statistically significant at 10%.