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Ethnic Social Network in Public Housing Market in Singapore*

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Abstract

This paper investigates the ethnic social network in Singapore's resale public housing market using a unique dataset containing the Cash-Over-Valuation (COV) information for a sample of 73,107 resale public housing transactions from 2007 to 2012. We find that the COV per square meter (psm), which represents a premium above the "objective" housing value, significantly increases with the concentration of buyers' own ethnic group at a housing block level. The results imply that buyers value housing blocks with higher concentration of the same ethnicity group of households. However, the convexity in COV premium suggests that the premium is too large to be fully explained by usual ethnicity related factors, such as cultural amenities, preference for the own ethnicity group, and supply constraint. We find significant evidence supporting the preference matching between buyer and seller reinforced through the ethnic social network as a key factor explaining the incremental COV premiums. The ethnic social network value is only found in transaction prices, if buyers and sellers of the same ethnic group sharing a common preference to trade with each other. We also find a high volume of the within-ethnicity-group transactions both in the own-ethnicity concentrated blocks and the other-ethnicity concentrated blocks, which is consistent with the ethnic social network hypothesis. A potential disconnection due to ethnic-based matching in the search process may cause segregation in the housing market.

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1. Introduction

Racial, or ethnic, segregation is a sensitive social issue in multi-racial societies that often creates significant pricing impact on housing. The existence of racial segregation creates race-based distortionary price effects in many housing neighborhoods in the US (King and Mieszkowski (1973)). Being a social sorting phenomenon, households' willingness to pay higher prices to live with peers in the same ethno-linguistic group is found in Canada (Li (2014)). In Singapore, the government has put in place policies to deliberately curb segregation in the public housing market. It imposes ethnic-based supply quotas to prevent segregation by selected ethnic groups at the block and precinct (neighborhood) levels and, as a result, creates significant pricing impact (Wong (2013, 2014)).

Why do households pay premiums for houses in segregated neighborhoods? What are possible channels/mechanisms that drive the ethnic-related housing price premiums? Various supply-side and demand-side factors have been studied in the literature. The supply-limiting mechanisms, such as the Ethnic Integration Quota (EIQ) policies on public housing in Singapore (Wong (2013, 2014)) and the Whites' discriminatory renting practices in the US (King and Mieszkowski (1973)), push housing prices up in segregated neighborhoods.

There are two standard explanations for the price premium driven by demand-side segregation. First, households prefer to live near both "hard" and "soft" ethnic-specific amenities. The "hard" ethnic amenities, such as schools, places of worship, markets and others, are orthogonal to the ethnic-neutral physical and spatial (location) variables usually found in standard hedonic housing models. The "soft" ethnic amenities are activity-based social interactions, such as sharing the same cultural interests, following the same religious faiths, and/or joining the same social events including classes in dancing, Taiji and various sports etc. Second, households prefer to live in blocks with more neighbors of the own ethnicity group, and derive incremental utilities from purely interacting with the own ethnicity group neighbors (Wong (2013)).

In this paper, we aim to investigate the ethnic social network as a demand-side driver

on households' residential location choice using a unique set of public housing transaction data in Singapore. Here, the ethnic social network is a network within an ethnic group, i.e. Chinese, Malay, or Indian, that promotes transactions within the ethnic group and the ethnicspecific preference matching. Being a multi-racial society with three major ethnic groups, Singapore provides several advantages to test the effect of the ethnic social network. First is the clean identification of the ethnicity of buyers and sellers in the transactions. Second is the existence of "cash-over-valuation" (COV) practice, which isolates unobservable value of subjective preference in transactions.

In Singapore's resale public housing market, it is a common practice for a seller to obtain valuation on his/her house, and use the information to negotiate with a prospective buyer and arrive at an agreed resale price. Our unique dataset contains both the transaction price and also the corresponding "objective" value¹ determined by a professional appraisal for each sample house. The difference between a transaction price and a valuation is known as "cash-over-valuation" (COV).² COV is an equilibrium value negotiated between a buyer and a seller; and it is independent of values for observable physical and location attributes. The buyer can only pay the COV in cash; he can neither use savings in his/her pension savings in the Central Provident Fund (CPF) account³, nor take additional loans from a commercial bank to pay for the COV. Therefore, the COV is unique to each transaction; and it captures unobservable values associated with social amenities, and other segregation-based factors, such as ethnic social network. In this study, we match this unique COV data in public resale housing

¹The objective value of a house is usually not observed ex-post in the data; but the literature uses standard hedonic housing models to predict the objective prices, which should be correlated with the objective values of the sample houses, if observable variables on physical and spatial attributes are well represented in the models. Instead, we use the exact objective value that is actually used for negotiating transaction price.

²The cash-over-valuation practices have been disallowed by the Housing and Development Board (HDB), the public housing authority of Singapore, with effects from 10 March 2014. A request for valuation is only allowed after the option to purchase is granted by a seller to a potential buyer; and a seller can no longer use the valuation information to negotiate up final prices. However, as the policy implementation date falls outside our sample period, we cannot use the policy shock in our experimental designs.

³The CPF scheme is a compulsory scheme, which is set up to meet the medical, housing and retirement needs of Singaporeans and permanent residents. Employers and employees are required to mandatorily contribute 37% of their gross income (employer: 17% and employee: 20%) as of 1 January 2016 for those below 55 years into their respective CPF accounts.

transactions to the personal demographic data of Singaporean residents, and use the matched dataset to test for significance of social proximity premiums associated with cultural amenities and ethnic social network.

Based on a sample of 73,107 resale public housing transactions with the COV data covering the period from 2007 to 2012, we find that COV per square meter significantly increases in housing blocks with a high concentration of buyers' own ethnicity group. Using the ethnicity quota as a discrete measure for the high ethnicity presence, we find that COV per square meter significantly increases in housing blocks with the own ethnicity quota, but decreases in housing blocks with the other ethnicity quota. Chinese buyers pay additional COV of SGD44.20 per square meter for units in blocks with the Chinese quota, but pay SGD11.30 less in COV in blocks with Malay quota and SGD36.48 less in COV in blocks with Indian quota. We find similar results for Malay buyers and Indian buyers. The COV premiums for the own ethnicity quota and also the COV discounts for the other ethnicity quota cannot be explained solely by the supply constraint (quota-binding) story. We next use the fraction of ethnicity group in a block as a continuous measure for the ethnicity presence, and find that COV per square meter (psm) increases significantly and monotonically with the fraction of buyers' own ethnicity group at a block level. We find that Chinese buyers pay SGD2.09 more in COV (psm) for every 1% increase in Chinese residents in a block, SGD2.05 less in COV (psm) for every 1% increase in Malay residents in a block, and SGD1.91 less in COV (psm) for every 1% increase in Indian residents in a block.

Buyers pay COV (psm) premiums for the presence of a high fraction of ethnicity (either discretely or continuously) of the same group as the buyers. However, the ethnicity preference and ethnic amenities factors alone can not fully explain the convexity in the premiums. First, using Singapore's public housing market as a natural experiment setup, Wong (2013) finds that buyers' willingness to pay for ethnicity presence is an inverted U-shaped curve, such that an addition of a new neighbor of the same ethnic group reduces the price controlling for additional amenities associated with the new neighbor. The preference for neighbors of the same ethnicity group itself is unlikely to cause the convexity (exponential increases) in the COV premiums. Second, ethnic-specific amenities increase with the concentration of a specific ethnicity group in a block. But, in a typical self-contained public housing estate in Singapore, the supply of local amenities, such as schools, supermarkets, clinics, hawker centres, sports and recreational facilities is highly inelastic. Lands set aside for the amenities are limited; and thus new ethnic-based amenities are not likely to increase proportionally with demand. The ethnic amenities factor is thus not likely to explain the convexity in COV premiums.

This study hypothesizes the ethnic social network as one possible factor driving the convex relationship between COV premium and ethnicity concentration in a housing block. The sharing of "taste" in things like interior design and social amenities improves preference matching between buyer and seller. The ethnic social network increases the ethnic preference matching propensity in a housing block (neighborhood) with high concentration of the own-ethnicity group, and in turn, supports the convex COV premiums. To investigate the effects of ethnic social network, we construct the repeated-sale samples based on housing units sold twice, 99 units sold for 3 times, and 3 units sold for 4 times in our samples. For each pair of the repeated housing transactions, we identify the ethnicity of seller based on the buyer's ethnicity of the same unit in the previous sale. We are able to match the buyer and seller information for 3,859 repeated transactions, which include 289 cross-ethnicity transactions, and 3,570 within-ethnicity transactions.

If the COV premiums are purely attributed to ethnic amenities and/or preference for the own ethnicity in neighborhoods, buyers should not care about the ethnicity of sellers whom they buy the units from. Using the repeat-sale samples, we find that having a buyer being matched with the ethnicity quota, for example, having a Chinese buyer in a Chinese quota housing block, and/or having a buyer being matched with the high ethnicity fraction, for example, a Chinese buyer in a high Chinese concentration block, are both not sufficient conditions to generate a large (convex) COV premium. However, the within-ethnicity transactions, where buyers and sellers are from the same ethnicity group, are a necessary condition to generate COV premiums that are exponentially correlated with the block-level ethnicity concentration.

While the ethnic social network via the ethnic preference matching explains the convex COV premium, it also has an implication on the trading volume. Matching of the ethnic-specific taste should increase the propensity of buyer and seller of the same ethnicity group to trade; and higher COV premiums in the transaction should reflect the ethnic-specific values. Using all the repeat-sale samples, we first find that transactions are highly concentrated in the within-ethnicity group. 94.2% of Chinese buyers (2583 out of 2741) purchase units from Chinese sellers, 83.6% of Indian buyers (188 out of 225) purchase units from Indian sellers, 91.7% of Malay buyers (778 out of 848) purchase units from Malay sellers. The concentration is even higher in blocks with the own-ethnicity quota as we expect. Chinese buyers purchase units mostly from Chinese sellers in the Chinese quota binding blocks (98%). Combined with the existence of significant COV premiums in the within-ethnicity transactions in own (Chinese) quota binding blocks, this provides supportive evidence for the preference matching story to support the ethnic social network hypothesis.

Ethnic preference matching in ethnic social network may seem similar to information spillover story that happens among people speaking in the same language and/or with the same education background (Bertrand et al. (2000)). The evidence so far coincides with the case of ethnic-specific information flowing through the network. Interestingly, we also find the same high concentration in other ethnicity buyers in blocks with Chinese binding quotas. In these Chinese quota binding blocks, 81% of Indian buyers purchase units from Indian sellers, and 90.1% of Malay buyers purchase units from Malay sellers. Unlike Chinese buyers who pay COV premiums, Indian buyers and Malay buyers pay COV discounts for the within-ethnicity group transactions in the Chinese quota binding blocks, which is inconsistent with the early preference matching and information spillover stories. This suggests the effect of pure ethnic social network after controlling for the preference matching and/or information spillover effects. That is, the effect of pure ethnic social network simply increases the intensity of the within-ethnicity transaction without having any premium associated with it. For example, using the same real estate agents may increase the intensity, but may not necessarily increase the COV in the within-ethnicity transactions.⁴ Or buyers and sellers may still be more comfortable to communicate in their own native languages in housing transactions though English is a prevalent business language spoken in Singapore's society. The effect of pure ethnic social network implies that the search friction in the housing market is one possible factor contributing to racial segregation in the housing market.

This paper makes three contributions to the housing segregation and social interactions literature. First, it is closely related to the studies on "taste for segregation" and pricing of social amenities in housing markets. Wong (2013) finds significant distortionary pricing effects caused by ethnic quota constraints in the Singapore's resale public housing market. However, due to data limitations, she was not able to match the buyer and seller's ethnicity in transactions to further pin down possible channels driving cultural value from social interactions in housing choice decisions. Second, the paper contributes to the economic behavior literature examining social interactions in activities ranging from financial decision (Hong et al. (2004), Madrian and Shea (2001), Duflo and Saez (2002)) to social problems (Case and Katz (1991), Glaeser et al. (1996)). We find new evidence of social interactions in explaining high concentration of the within-ethnicity transactions in both the own-ethnic quota binding housing blocks, and also the other-ethnic quota binding blocks. Third, the paper contributes to the bargaining power literature of Harding et al. (2003), who find that bargaining power of buyers and sellers are race-neutral. We, however, find evidence to suggest that social interactions, though unobservable, add significant premiums in housing prices through the preference matching effects, such as sharing of common "taste" or social amenities.

The paper is organized as follows: Section 2 reviews the housing literature on ethnic segregation, and the broader literature on social interactions. Section 3 gives relevant information

 $^{^{4}}$ There are real estate agents and web-portals targeting only at selected ethnicity group. The withinethnicity effect is reinforced through these communication channels.

on institutional features including the COV practices in the public housing market in Singapore. Section 4 covers data descriptions and derivations of key variables. Section 5 discusses the empirical methodologies. Section 6 analyzes empirical results. Section 7 concludes the paper with discussions of relevant policy implications.

2. Literature Review

In *laissez-faire* private housing markets, where supply and demand are unregulated, racebased discriminatory price effects exist in neighborhoods with the racial segregation (King and Mieszkowski (1973)). There are two mechanisms causing price distortions in segregated neighborhoods. The supply-side mechanism, if left alone, is not likely to produce enough housing stocks to meet the demand by different ethnicity groups. If housing stocks were segmented, increased demand by one ethnicity group in a sub-market is not likely to be met by housing stocks of a different ethnicity group in another sub-market. White landlords' reluctance to rent housing units to black tenants aggravates supply inelasticity and drives up rents in the black housing sub-market (King and Mieszkowski (1973)). As a result, the housing markets become segregated. In some countries, governments use race-based quotas to encourage desegregation by deliberately restricting allocation of housing units to selected ethnicity groups (Wong (2013, 2014)).

The demand-side mechanism induces sorting by residents causing segregation along the ethnicity line. There are at least, but not exhaustively, three possible explanations for the demand-induced segregation in the economic literature. First, King and Mieszkowski (1973) argue that the "taste for segregation" by the whites relative to the "taste for integration" by the blacks causes spatial variations in housing prices in the white and the black neighborhoods. Segregated neighborhoods with a high concentration of a selected ethnicity group usually attract more social and cultural amenities preferred by the dominant ethnic group (e.g. places of worship, events and activities organized in the communities, etc.) (Li (2014)). The literature

usually capitalizes the "taste of preference" into housing prices via the homogeneity in ethnic composition (Coulson and Bond (1990); Macpherson and Sirmans (2001); Patrick and Kahn (2005); Fu (2005); Clapp et al. (2008); Saiz and Wachter (2011); and Li (2014)), though solving endogeneity issues remains a main concern. In this paper, we find that the matching ethnic preference in the within ethnicity transactions is a key to create price premium associated with ethnic amenities.

The second explanation is related to peer effects and social networks. The literature argues that social interactions lead to two possible outcomes. One is related to information spillovers (social network) (Bertrand et al. (2000)) and another is on conformance of a social norm.⁵ It is empirically challenging to find an identification strategy that can separate the causal relations between peer group behavior and individual behavior (Manski (1993)). Residents from the same ethnic group, who share similar preferences, tend to gather in a neighbourhood with selected ethnic-specific amenities. Therefore, it is hard to tell if individuals' housing choice is influenced by their peers in a neighbourhood. Most studies in the literature that examine peers' information interventions on individual behaviour could not reject the peer norm in housing market, which are reflected in premiums paid for ethnic amenities in segregated neighbourhoods. In this paper, we find evidence that the ethnic social network matters even after controlling ethnic amenities and information spillovers.

The third demand-side segregation effect is more closely related the bargaining story (Harding et al. (2003)), but, to a lesser extent, related to information spillover (Bertrand et al. (2000)). Fisman et al. (2017) show that social affinity and ethnic proximity generate information benefits that outweigh mis-allocation costs of taste-based discrimination in loan outcomes using loan data from an Indian bank in the study. In this paper, we find the evidence of existence of an ethnic social network that is not related to information spillover or information friction.

⁵A growing literature documents peer norms in disparate economic activities, which include retirement saving outcomes (Duflo and Saez (2002, 2003); Beshears et al. (2015)), stock market parcipation (Hong et al. (2004); Brown et al. (2008)), corporate compensation and merger practices (Bizjak et al. (2009); Shue (2013)), entrepreneurial risk-taking (Lerner and Malmendier (2013)), and risk aversion (Ahern et al. (2014)).

3. Institutional Features in the Public Housing Market in Singapore

In Singapore, public housing market provides houses for more than 80% of the population, which as a result, contributes to the high home ownership rate of nearly 90% in the islandstate. The Housing and Development Board (HDB) is Singapore's housing authority that is responsible for the supply of public housing in the primary market, where public housing flats are sold at concessionary prices to eligible residents. Currently, only Singaporean with a monthly income of below \$12,000 are eligible to buy subsidized housing flats directly from the HDB. Besides the regulated primary public housing market, there is also a parallel resale (secondary) market that operates in a laissez-faire environment, via which Singaporean and permanent residents, who can not meet the eligibility criteria, can buy public housing flats at market prices. Singaporean homeowners can sell their housing flats in the resale market after fulfilling the minimum 5 years of occupation requirement.

There are two institutional features in the public housing market in Singapore that are important for our experiment set-up, which include the Cash Over Valuation (COV) and the Ethnic Integration Policy (EIP). The followings provide more details on these two features:

3.1. Cash Over Valuation (COV)

The COV phenomenon is unique to the secondary public housing market in Singapore. Prior to 2014^6 , it was a common practice for public housing owners to request to obtain an appraisal of their housing flats from a panel of accredited appraisals (valuers) in the sale process. Based on the valuation, they negotiate with prospective buyers to arrive at agreed transaction prices.

In the appraisal process, professional appraisals use past transactions of comparable houses and make adjustment with respect to observable factors, which include housing attributes

⁶The HDB passed a new policy to ban the COV practices with effect from 10 March 2014, whereby requests for an appraisal will not be allowed prior to the signing of an option to purchase (OTP); and the COV information will no longer be made public by the HDB after the date.

(such as unit size, age, etc.) and location and neighborhood amenities (such as distances to nearby primary schools and subway stations, etc.), when determining the value of a subject house. The appraisal process is likened the standard hedonic models, where quality-adjusted predicted prices (*objective* value) are estimated. Unobservable factors, such as cultural amenities or social interactions within ethnicity groups, which are also key price determinants, are, however, neglected in the derivation of *objective* values for subject houses.

Difference between the final agreed price (which is considered as a willing-buyer's and a willing-seller's price that is freely negotiated and determined on "a willing buyer and a willing seller" basic, or the *subjective* value) and the appraisal value (the *objective* value), if existing in a transaction, is known as the COV in resale public housing market. Therefore, COV captures marginal premiums that potential buyers pay for factors other than hedonic attributes and neighborhood amenities; and these factors may include intensity of social interactions and cultural amenities.

A buyer is expected to pay the COV, or the cash premium by cash in an arm's length transaction. Note that paying COV is not a necessarily condition for a resale purchase. The public housing agency, Housing and Development Board (HDB), comments in its InfoWEB that "resale price may be above, at or below market valuation depending on the outcome of negotiation between a buyer and seller, and there is no need to pay any COV should the resale transaction be at or below market valuation of the unit"⁷

Due to the large sum of upfront cash payment, the COV is economically burdensome to buyers. Buyers obtain loans from either HDB or commercial banks when they purchase public housing but the loans do not cover the COV payment. In case of HDB loans, the appraisal values are considered as the *fair value* by the HDB, when granting concessionary interest rate loans to buyers.⁸ HDB caps the loan ceiling at 90% of the sale price or the appraisal value,

⁷HDB InfoWeb, "Median Cash-Over-Valuation (COV) by Town and Flat Type," September 2011. Source: https://weaponlcp.files.wordpress.com/2011/09/cov.pdf

⁸The HDB concessionary interest rate is pegged at 0.1% above the long-term saving rates of the CPF Ordinary Account (the rate has remained constant at 2.5% since 1993), and the loan term is capped at 25 years. With effects from 28 August 2013, the loan to value ratio for commercial bank loans is capped at 80%, based on the sale price or the appraisal value, whichever is lower; for loans with a payment term of below 25

whichever is lower. However, the 90% HDB loan ceiling is hardly met in practice, because the loan is only disbursed after a borrower has drawn down all the savings in his/her Central Provident Fund (CPF) Ordinary Account to reduce the loan quantum (excluding COV). COV will need to be paid out from his own cash reserve.

Buyers could also consider commercial bank loans as an alternative, which usually offer more flexible and competitive terms. The interest rates are usually pegged to selected market interest rate indicators. Like HDB, commercial banks also use the appraisal values to determine loan quantum for granting loans (with a loan term of less than 25 years), which is currently set at 80% of the market price or the appraisal value, whichever is lower (with effect from 28 August 2013). For the remainder 20% of the (appraisal) value (if lower), a borrower is required to make a minimum 5% of payment in cash, and he/she can use his savings to pay for the balance of 15% of the value, provided there were sufficient savings in his/her CPF Ordinary Account. This means that for a resale public housing flat buyer who chooses a commercial bank loan, he/she needs to fork out a sum of cash upfront to pay for the COV⁹, if positive, and the 5% payment, which is not covered by a bank loan, nor by his/her CPF savings.

COV in the resale HDB market provides a significant indicator of housing affordability, where potential buyers, who do not have enough upfront cash are likely to be excluded from the market. The positive COV trend has persisted in the resale public housing market since 2007 (Lee and Yeo (2013)). The rising COV has triggered concerns of many buyers, especially younger ones, for making public resale housing more unaffordable. The government, however, was mindful about *unreasonable* demand for high COV by some sellers, which could drive prices off the fundamental. On March 11, 2014, HDB acted by scrapping the COV practices, stopping sellers from obtaining an appraisal report for their flats and use it as a base price to negotiate with buyers on the sale price.¹⁰ The appraisal report could only be obtained after

years.

⁹He/she is not allowed to use CPF savings to pay for COV.

¹⁰Sumita Sreedharan, "HDB resale: Parties must agree on price before valuation," Today Online, March 11, 2014.

the two parties have agreed on the final sale price.

3.2. Ethnic Integration Policy (EIP)

On March 1, 1989, Singapore government introduced the Ethnic Integration Policy (EIP) aimed to prevent the formation of racial enclaves in the public housing estate. As a multiracial society, the government takes a strong stand on maintaining a balanced mix of ethnic groups at the neighborhood and within the block levels, which is deemed to be a key to fostering harmonious living among ethnic communities in public housing. The allocation of new public housing flats adheres strictly to the neighborhood and block quotas set for each ethnic group as in Table 1. Being the largest ethnic group in the country, the Chinese ethnic quotas are set at 84% and 87% at the neighborhood and block levels, respectively. The Malay ethnic enclave must not exceed 22% and 25% at the neighborhood and the block levels, respectively. With effect from 5 March 2010, HDB increased the Indian/Other ethnic group limits from 10% to 12% at the neighborhood level and from 13% to 15% at the block level.

During the selection of new flats, buyers of a selected ethnic group will not be allowed to book a flat, if the ethnic quota has been reached. The EIP also applies to resale flats and rental flats built by HDB. We identify those housing blocks with ethnic ratios (concentration) exceeding the ceiling stipulated for the respective ethnic groups as quota binding blocks. For example, in a Chinese-quota binding block having a Chinese residents' concentration at or above 87%, a prospective Chinese buyer is not allowed to buy a resale housing flat from a non-Chinese seller within the block. However, this Chinese buyer could still buy a resale flat from another Chinese seller within the block. Wong (2013, 2014) use the EIP setup in Singapore exploiting the discontinuous price around the threshold for her studies.

4. Data

We obtain the data of public housing resale transactions in Singapore for the period of 2007 to 2012 from Singapore Real Estate Exchange (SRX), a commercial real estate information exchange that is formed by a consortium of 16 leading real estate agencies in Singapore (as of December 2016). The data consist of information on date of transaction, appraisal price, COV, and information on housing attributes, such as address, postal code, floor, unit size, and property type. We merge the HDB resale transaction data with a large proprietary database of more than 2 million Singaporean residents. The data contain detailed personal demographic information that identifies buyer attributes for all household members, such as gender, race, and date of birth .

4.1. Ethnicity of Buyers

Since transactions are by household, we need to construct household-level ethnicity. Using the individual-level ethnicity and date of birth data, we set up our identifications of the ethnicity of buyers in our databases. For each resale transaction, we construct the household-level ethnicity indicator using following rules: First, if all members in a family (as identified by a common home address and transaction) are from a same ethnicity group, we assign the ethnicity to the household/family. For example, if all members in a family are Chinese, we define the household as a Chinese household. One ethnicity household constitutes about 89% of the resale transaction sample. Second, for families with mixed ethnicity members (which could be due to cross-ethnic marriage), we assign the ethnicity based on the majority ethnic group in the households, which is defined as having more than 50% of the transaction sample in the data. Third, if the number of family members are tied between two ethnicity groups, we follow the ethnicity identity of the eldest member in the household. This sample group constitutes about 4% of the sample households in the data. We drop the remainder of about

1% of the sample, of which we cannot assign the household-level ethnicity following the above rules. After removing data with incomplete information on COV, unit size, and ethnicity, we retain a final sample of 73,107 transactions for our empirical analyses.

4.2. Summary Statistics

Table 2 reports the summary statistics for the full sample of 73,107 resale public housing transactions. Panel A shows the distributions of transactions by buyer ethnicity, which consist of 53,229 transactions by Chinese buyers (72.81%), 15,184 transactions by Malay buyers (20.77%), and 3,801 transactions by Indian buyers (5.2%).

Panel B reports the summary statistics for variables of interest. The appraisal price is, on average, estimated at Singapore Dollar (SGD) 382,406, and the value ranges from SGD169,000 to SGD750,000.¹¹ The average COV is estimated at SGD24,136, which is about 6% of the average appraisal price. COV varies widely from -SGD22,000 to SGD90,000. The appraisal value per square meter is estimated at SGD 3,927, on average; and the COV per square meter (COV (psm)) is estimated at SGD 253, on average. Given the high-density nature of Singapore's public housing, the average floor level (height) is 7.55, and it ranges from 1 to 40. The average unit size is 99 square meters (sqm); and it ranges from 31 sqm to 243 sqm.

Figure 1 reports the histogram of COV (psm). Vertical red-dot line indicates the average COV (psm), which is SGD253. We first find significant fraction of transactions at zero COV (psm), indicating that many of transaction prices equal to objective valuations. We next find that COV (psm) is most likely to be positive. If the buyer and seller matching is random and COV (psm) is an idiosyncratic noise, we should observe symmetric distribution around zero.

Figure 2 show the monthly time-series plots for average unit COV (psm) (dashed line) and the average ratio of COV to total transaction price (solid line). Here the transaction price is the sum of appraisal value and COV. We find significant time variation in COV (psm) from SGD43 to SGD412 during the sample period. The ratio of COV to total transaction

¹¹Appraisal Value and COV are winsorized at the 1% level on both tails for robustness.

price shows the weightage of COV in total transaction price, which ranges between 1% to 8% during the sample period. Note that the time-series variation in COV (psm) shows similar pattern with the time-series variation in the ratio of COV to total transaction price. That is, the fluctuation in transaction price is mostly coming from the fluctuation in COV.

Panel B of Table 2 also reports the summary statistics of other typical variables that may affect the value of properties. First is the distance to nearest MRT. This is the linear distance of the sample housing block to the nearest mass rapid transit (MRT) station; and the average distance is 890 meters, and ranges from 4 meters to 3,520 meters. Second is the quality of primary school education, where the distance-based allocation policy is implemented by the government for selected school placements (Agarwal et al. (2016)), by sorting the home-school distances into two categories: (a) housing blocks within 1 kilometre (km) radius from the school; and (b) housing blocks between 1 km and 2 km. We measure a school quality, based on the Primary School Leaving Examination (PSLE) results¹² and average the rankings of primary schools located within 1 km and 1-2km into the primary school quality indices by blocks. Note that higher Primary School Quality indicates better primary education around the blocks and there are some blocks without any primary school within 2km.

Panel C of Table 2 reports on distributions of the sample transactions sorted by property type. HDB classifies the housing type by the room number into 1-bedroom to 5-bedroom types, and other large flat types, such as "HUDC", "Jumbo" and "Executive". 4-bedroom flats is the most popular housing type constituting about 37% of the total transactions, followed by 3-bedroom and 5-bedroom housing types constituting 26.48% and 26.39% of the total transactions, respectively.

¹²We use the data published by a commercial online education consultant in Singapore, "Kiasuparents.com", and construct the School Quality Index using the (standardized) academic performance score. Source: "https://www.kiasuparents.com/kiasu/article/singapore-primary-schools-ranked-by-academic-excellence/".

4.3. Ethnicity Concentration

From the proprietary resident database¹³, we construct household-level ethnicity for all residents in blocks applying the same rules as above and aggregate them into two block-level variables: the quota-binding indicator and the segregation measures (by fractions of residents of selected ethnicity groups).

In Singapore, the postal-code system assigns a unique 6-digit postal code for each housing block; and there are a total of 8,194 blocks each identified by a unique postal code in the resident database. Based on the postal-code identifier, we construct the ethnicity measures based on the fraction of Chinese, Malay, and Indian residents in the total resident sample sorted at the block-level and by year. The composition of Singapore's residents by the ethnicity group has remained rather stable since independence in 1965 as in Figure 3, with Chinese forming the majority group, followed by Malays and Indians. The ethnic composition ratios are estimated at 74.4%, 13.5%, and 9.1%, respectively, during the our sample period 2007-2012. The block-level ethnic ratios are also almost time-invariant. Based on our resident database, we report the summary statistics of the fractions of ethnicity in blocks in Panel A of Table 3. The median ratio for Chinese is slightly higher at 81.38%, followed by 13.89% for Malays, and the median of 3.33% for Indians is lower than the national average.

As discussed in the early section, the EIP, existed since 1989, has played an instrumental role in upholding racial harmony and integration in Singapore. When a block quota is binding for a selected ethnic group, any transaction that increases the ethnicity presence in a block will not be approved by the HDB. Having an ethnicity quota in a block means that the block is at the right-tailed distribution in term of the ethnicity presence. We define block-level quota-binding indicators that serve as an alternative discrete measure of the ethnicity segregation (high concentration) in a block, which supplements the continuous block-level ethnic ratio measure. If more than 87% of the residents within a block is composed of Chinese, the block

¹³The database covers more than 2 million of Singaporean citizens and permanent residents living in Singapore. The database provides demographic and ethnicity details of household members, who are above 18 years old.

is identified as the Chinese quota-binding block, and non-Chinese households from the same block cannot sell their units to Chinese buyers. There are 2,280 blocks (postal codes) with Chinese quota-binding constraints out of 8,194 blocks, which are top 25% blocks in Panel A of Table 2. The Malay quota is set at 25% and 1,368 of the blocks (about top 10% blocks) are subject to the Malay-quota-binding constraints, such that Malay households in these blocks could not sell their public housing flats to non-Malay buyers. For Indians, the quota has been raised from 13% to 15% with effect from March 12, 2010; and only 90 blocks are subject to the Indian-quota-binding constraints before the change, and 71 blocks face the quota-binding constraints after the quota has been revised in 2010. Ethnicity quotas are also widely spread in Singapore as in Appendix Table 1.

Panel B of Table 3 reports the determinants of ethnicity presence in blocks. Columns (1)-(3) show the results using fractions of ethnicity group as dependent variables. In column (1), dependent variable is the fraction of Chines in a block. Independent variables are Distance to nearest MRT, Primary School Quality, Average Unit Size in a block, and Maximum floor in a block. We find that the fraction of Chinese increases with shorter distance to MRT, better primary school quality, higher the maximum floor of the building, and more smaller sized unit in a building. Column (2) reports the result with the fraction of Malay as dependent variable. We find that the fraction of Malay increases in an opposite direction from Chinese: longer distance to MRT, poorer primary education quality, and lower height of building. Column (3) reports the result with the fraction of Indian as dependent variable. Indian fraction increases with shorter distance to MRT, but decreases with school quality and height of building.

Columns (4)-(6) show the logit results using ethnicity quota as dependent variable. Column (4) reports the result for Chinese quota, column (5) reports result for Malay quota, and column (6) reports result for Indian quota. We find similar results as in columns (1)-(3). That is, on average, the blocks with higher Chinese presence are more valuable blocks: closer to MRT, better education quality, and higher building. This partially explains why Chinese buyer pays highest price on average.

5. Empirical Methodology

The identifications of the ethnicity of buyers, the EIP (desegregation) policy and the presence of COV are unique institutional features in Singapore's resale housing market that jointly contribute to the setting up of a clean natural experiment to empirically test economic values of cultural affinity and social interactions.

The COV data are unique to Singapore's housing market. Defined as differences between resale transaction prices and appraisal values, the COV data are used in our study to directly disentangle values associated with observable and unobservable factors. Professional appraisals use past transactions of comparable houses to derive *objective* values for houses taking into account observable physical and neighbourhood attributes, whereas the *subjective* transaction prices that match a buyer's willingness to pay and a seller's price expectation capture other factors that are not directly observed in the appraisal process. These are not idiosyncratic factors, or random errors in distributions that can be cancelled out, on average; but they are orthogonal factors that matter in buyer-seller negotiations. These unobservable factors potentially include "taste for segregation" and social interactions that are specific to unique to buyers of selected ethnicity groups. For example, a Chinese buyer may pay more for a house from a Chinese seller, because interior decoration or designs of the house are closer to his/her taste and preference.

In our empirical models, we use two variables to represent the ethnicity presence within a public housing block. First, we use a discrete variable to identify housing blocks with a binding ethnicity-quota, which has a value of 1, if a block is subject to the ethnicity quota constraint, i.e. the existing ethnic ratio has reached the limit set by the EIP; and 0 otherwise. Second, we use a continuous measure which is the fraction of households of a selected ethnicity group in each block. Note that the continuous variable on ethnicity fraction captures the monotonic increase in intensity of social interactions associated with the ethnicity presence in a block; whereas, the ethnic quota captures the discontinuity in the social interaction at the threshold of the ethnicity quota.

If the value of social interaction exists, it will be materialized through the buyers' and sellers' willingness to trade, COV_{psm} , if the buyer is from the ethnicity group. We use both of measures for the block-level ethnicity presence independently, and interact the variables separately with an indicator for buyer ethnicity to quantify the economic effects of social interaction. The buyer ethnicity indicator has a value of 1, if a housing is bought by a buyer of the defined ethnicity group k, where k = [Chinese, Malay, and Indian]; and otherwise 0. With COV_{psm} as dependent variable, the model specification is written as:

$$COV_{psm} = \alpha + \beta \cdot X_{i,t} + \gamma \cdot I_{BuyerEthnicity} + \psi \cdot \text{Ethnicity Presence} \times I_{BuyerEthnicity} + \lambda_b + \tau_t + \epsilon_{i,b,t}$$

where $X_{i,t}$ is a vector of regressors for hedonic attributes, such as unit size, floor, and property type dummy. λ_b is the block fixed effects and τ_t is the year and month fixed effects that are included to control for spatial heterogeneity and time variations, respectively, in the models. Due to block fixed effect, block-level Ethnicity Presence variables are not estimated. But the interaction term, [Ethnicity Presence $\times I_{BuyerEthnicity}$], still can be identified separately for the three ethnicity groups of buyers: Chinese, Malay and Indian.

While our original transaction data do not contain seller identities, we could, however, infer the sellers' demographic details from repeated transactions, i.e. houses that sell at least twice during the sample period. In the repeated sale samples, the buyers in the first sales (or the early sales, if sold more than twice) are deemed to be the sellers for the subsequent (repeated) sales. The buyer demographic information including ethnicity from the first sales are used to identify sellers' profiles. We construct an ethnicity matching indicator that has a value of 1 for within-ethnicity transactions between buyers and sellers of the same ethnicity group; and 0 otherwise for cross-ethnicity transactions, if buyers and sellers are from different ethnicity groups. The within-ethnicity indicator is used as a proxy for the preference matching or information spillovers within ethnicity in the housing search process in the model.

We extend our analyses by replacing the $I_{BuyerEthnicity}$ in previous specification with the

Within Ethnicity dummy, and test the differential effects of the "peer" or "ethnicity" preference matching on buyers' COV_{psm} in housing transactions with respect to ethnicity presence in housing blocks. As in the previous specification, we use two different measure of ethnicity presence: ethnicity quota and the fraction of ethnicity in a block. The model specification is written as:

$$COV_{psm} = \alpha + \beta \cdot X_{i,t} + \gamma \cdot I_{WithinEthnicity} + \psi \cdot \text{Ethnicity Presence} \times I_{WithinEthnicity} + \tau_t + \epsilon_{i,b,t}$$

where $X_{i,t}$ is a vector of regressors for hedonic attributes, such as unit size, floor, property type dummy, distance to nearest MRT, primary school quality around the block. τ_t is the year and month fixed effects that are included to control for time variations in the models. Due to the sample size issue, we do not include block fixed effect in this specification but we add block-level controls to account for other factors that may affect on COV (psm).

The preference matching effect will be significant in explaining variations in COV_{psm} , if buyers of the same ethnicity group are able to improve likelihoods of preference matching in resale transactions to agree on higher COV_{psm} . The effects are also expected to be larger for transactions with higher ethnicity presence i.e. ethnic quota-binding blocks or high ethnicity fraction in a block.

6. Empirical Results

6.1. Ethnicity Presence and COV premium

We use the full sample of resale public housing transactions to test the COV premium associated with ethnicity presence in a block. Two variables are used to represent the presence of an ethnicity group at the block level in the models: 1) a dummy variable on the presence of binding ethnicity quota in a block and 2) the fraction of an ethnicity group in a block. We interpret the ethnicity-binding quota indicator as a measure of discontinuity at the tailed-end (extreme) of the distributions of ethnicity presence.

Table 4 shows the panel regression results on interactive effects of the buyer ethnicity and the ethnicity-binding quota dummy on the COV premiums. COV (psm) is the dependent variable, and the variable of interest is the interactive terms of buyer ethnicity (I_Buyer Ethnicity) and ethnicity quotas (I_Ethnicity Quota). Column (1) shows the result on Chinese buyers, where I_Buyer Ethnicity equals to 1, if the buyer is Chinese; and 0 otherwise. I_Buyer Ethnicity is interacted with dummy variables for ethnicity quota: I_Chinese Quota, I_Malay Quota, and I_Indian Quota. We include the block fixed effects. The ethnicity quota dummy variables are not estimated, except for the Indian Quota dummy with a time-series change in threshold in 2010. We include the year and the month fixed effects, and the property type fixed effects. Other independent variables include unit size and floor level.

We find that Chinese buyers pay higher COV (psm) of SGD44.20 for housing units in Chinese quota-binding blocks than non-quota blocks, but lower COV (psm) for housing units in other ethnic quota-binding blocks. Chinese buyers pay SGD11.30 and SGD36.48 lower in COV (psm) for housing units in Malay quota-binding blocks and Indian quota-binding blocks, respectively, relative to the control blocks without Malay and Indian quota-binding constraints. This indicates that Chinese buyers pay positive premiums only in the ownethnicity quota-binding blocks, but negative premium in other ethnicity quota-binding blocks. The control variables are all significant and with the correct signs. The negative coefficient on the size variable indicates diminishing effects of unit size on COV per unit area; and the positive coefficient on the floor (height) variable indicates high premiums for housing units at higher floors that are windy and have better view.

Column (2) shows the results on Malay buyers, where I_Buyer Ethnicity equals to 1, if the buyer is Malay; and 0 otherwise. We find that Malay buyers pay higher COV (psm) of SGD14.86 for housing units in Malay quota-binding blocks, but lower COV (psm) of SGD46.18 for housing units in Chinese quota-binding blocks. Malay also pays a positive premium in Indian quota-binding blocks; but the result is insignificant. But this effect is partly driven by the fact that 24 Malay quota-binding blocks are also Indian quota-binding blocks. Column (3) shows the results on Indian buyers, where I_Buyer Ethnicity equals to 1, if the buyer is Indian; ands 0 otherwise. We find that Indian buyers pay SGD57.34 lower in COV (psm) for housing units in Chinese quota-binding blocks. The COV premiums for housing units in Indian quota-binding and Malay quota-binding blocks are both positive, but statistically insignificant. Note that there are only 52 observations of Indian buyers in Indian quota-binding blocks in our sample.

Our results are unlikely to be related to the supply constraint story, which, if exists, should only apply to the "own" (same) ethnicity group in the quota-binding blocks, and not to other ethnicity group. For example, in a Malay quota-binding block, prospective Malay buyers (ownethnicity group) are not allowed to buy flats from non-Malay sellers, but the restriction does not apply to other non-quota binding buyers, such as Chinese. We find significant incremental effects in the own ethnic quota-binding blocks; and negative (opposite) effects in the other ethnic quota-binding blocks.

Table 5 reports the panel regression results on interactive effects of the buyer ethnicity and the (continuous) ethnicity fraction on the COV premiums. COV (psm) is the main dependent variable; and the variable of interest is the interactive terms of buyer ethnicity (LBuyer Ethnicity) and the ethnicity fraction in a block (Fraction of Ethnicity). Panel A reports the results with the block fixed effects. Columns (1)-(3) report the results on Chinese buyers. In Column (1), we interact LBuyer Ethnicity with Fraction of Chinese. Due to the block fixed effects, the Fraction of Chinese itself is not estimated. We include the year and the month fixed effects, and the property type fixed effects. We find that, on average, Chinese buyers pay SGD2.09 more in COV (psm) for every 1% increase in Chinese in the block. We interact LBuyer Ethnicity with Fraction of Malay in column (2) and with Fraction of Indian in column (3). We find that Chinese buyers pay SGD2.05 less in COV (psm) for every 1% increase in Malay in the block, and SGD1.91 less in COV (psm) for every 1% increase in Indian in the block. The unit size and floor level variables are all significant with the correct signs.

Columns (4)-(6) report the results on Malay buyers. In Column (5), we interact I_Buyer Ethnicity with Fraction of Malay. We find that, on average, Malay buyers pay SGD2.20 more in COV (psm) for every 1% increase in Malay in the block. We interact I_Buyer Ethnicity with Fraction of Chinese in column (4) and with Fraction of Indian in column (6). We find that Malay buyers pay SGD2.14 lower in COV (psm) for every 1% increase in Chinese in the block, and SGD1.70 more in COV (psm) for every 1% increase in Indian in the block.

Columns (7)-(9) report the results on Indian buyers. In Column (9), we interact I_Buyer Ethnicity with Fraction of Indian. We find that, on average, Indian buyers pay SGD0.59 more in COV (psm) for every 1% increase in Indian without statistical significance. We interact I_Buyer Ethnicity with Fraction of Chinese in column (7), and with Fraction of Malay in column (8). We find that Indian buyers pay SGD2.49 less in COV (psm) for every 1% increase in Chinese, and SGD2.68 more in COV (psm) for every 1% increase in Malay in the block.

Panel B of Table 5 reports the results without the block fixed effects. All the specifications are the same as in Panel A, except for the block fixed effects and additional block-level controls, such as distance to nearest MRT, qualities of primary schools within 1 km radius and within 1-2 km radius. Columns (1)-(3) reports the results on Chinese buyers. In Column (1), we interact LBuyer Ethnicity with Fraction of Chinese. Without the block fixed effects, we estimate the Fraction of Chinese itself. We also include the year and the month fixed effects, and the property type fixed effects. Other independent variables include unit size, floor level, distance to MRT, and quality of primary schools around the blocks. We find that, on average, Chinese buyers pay SGD2.26 more in COV (psm) for every 1% increase in Chinese in the block. We interact LBuyer Ethnicity with Fraction of Malay in column (2), and with Fraction of Indian in column (3). We find that Chinese buyers pay SGD2.29 less in COV (psm) for every 1% increase in Malay in the block, and SGD0.76 less in COV (psm) for every 1% increase in Indian in the block. The control variables are all significant and with the correct signs. We find positive premiums associated with shorter distance to MRT and better quality of primary school.

Columns (4)-(6) report the results on Malay buyers. In Column (5), we interact I_Buyer Ethnicity with Fraction of Malay. We find that, on average, Malay buyers pay SGD2.53 more in COV (psm) for every 1% increase in Malay in the block. We interact I_Buyer Ethnicity with Fraction of Chinese in column (4), and with Fraction of Indian in column (6). We find that Malay buyers pay SGD2.35 less in COV (psm) for every 1% increase in Chinese in the block, and SGD0.71 less in COV (psm) for every 1% increase in Indian in the block.

Columns (7)-(9) report the results on Indian buyers. In Column (9), we interact I_Buyer Ethnicity with Fraction of Indian. We find that, on average, Indian buyers pay SGD2.41 more in COV (psm) for every 1% increase in Indian in the block. We interact I_Buyer Ethnicity with Fraction of Chinese in column (7), and with Fraction of Malay in column (8). We find that Indian buyers pay SGD2.40 less in COV (psm) for every 1% increase in Chinese in the block, and SGD2.30 more in COV (psm) for every 1% increase in Malay in the block.

Using both the continuous ethnicity fraction variable and the discrete ethnic quota-binding variable, the results show positive and economically significant COV premiums that represent strong preference for social amenities and interactions in the public resale housing market. The results imply that buyers pay premiums above the appraisal ("objective") housing values to live close to neighbourhoods with a high concentration of households of the same ethnicity type. The COV premiums that capture the effects of social and cultural affinity are large, and persistent over time.

6.2. Convexity in COV premium

In the previous section, we find that buyers pay higher COV (psm) for ethnic presence of the own ethnicity group in a block. We next analyse the functional form of increments in the COV (psm).

First, we plot average COV (psm) paid by buyers of a selected ethnic group by the fraction of ethnicity presence and find a positive convex relationship between the COV (psm) and the fraction of own ethnicity group, but a negative concave relationship between the COV (psm) and the fraction of other ethnicity group. Panel A of Figure 4 reports the average COV (psm) paid by Chinese, Malay, and Indian buyers for each increment in the fraction of Chinese. We show non-parametric smoothing fit (locally weighted regression, LWR) on the scatter plots. The first graph shows the average COV (psm) that Chinese buyer pays for the fraction of Chinese residents in a block. The LWR fit shows a convex relationship between the fraction of Chinese and the COV (psm) that Chinese buyers pay. For Malay and Indian buyers as in the second and third graphs in Panel A, the relationships are negative and concave. Panel B reports the average COV (psm) paid by Chinese, Malay, and Indian buyers for each increment in the fraction of Malay. We find a convex relationship between the fraction of Malay in a block and the COV (psm) that Malay buyer pays. Chinese buyers and Indian buyers pay less COV (psm) as the fraction of Malay increases. Panel C reports the average COV (psm) paid by Chinese, Malay, and Indian buyers for each increment in the fraction of Indian. We find a weak convex relationship between the fraction of Indian in a block and the COV (psm) that Indian buyer pays. Chinese buyers and Malay buyers pay less COV (psm) as the fraction of Indian increases.

Table 6 reports the panel regression results of buyer's ethnicity and the presence of same ethnicity group in the block, and its square term. The dependent variable is COV (psm), and the variable of interest is the interaction between buyer ethnicity and the square term of the fraction of the ethnicity in a block. Columns (1)-(3) report the results with the block fixed effects. Column (1) includes a dummy variable for Chinese buyer (I_Buyer Ethnicity) and interactions of the Chinese buyer dummy with the fraction of Chinese and its square term. The independent variables include Size (sqm) and Unit Floor. We also include the year fixed effects, the month fixed effects, and the property type fixed effects. Since we have the block fixed effects, we cannot identify the effect of ethnicity fraction and its square term, but we can still identify the interactions. We find significant effect of the squared fraction of Chinese Ethnicity in a block on COV (psm), which supports the convex relationship between the buyer ethnicity and the fraction of own ethnicity in a block. This coincides with Figure 4. Column (2) is on Malay buyer, and column (3) is on Indian buyer. We find significant evidence of the convexity in the relationships. Columns (4)-(6) report results without the block fixed effects. Specifications are similar to columns (1)-(3) except for the block fixed effects and additional independent variables, such as distance to nearest MRT, primary school quality within 1 km radius and within 1-2 km radius. The results are similar to those found in (1)-(3). The control variables are all significant and with the correct signs.

How should we interpret the strong convexity in COV (psm) with respect to the fraction of ethnicity in a block? The positive COV (psm) premium associated with the high ethnicity presence (either discrete or continuous) may arise through many social interaction factors, such as ethnic amenities and social network. It is thus challenging to isolate a mechanism from the others. The first potential factor is the preference for ethnicity in the neighborhoods. Controlling for all other factors i.e. cultural amenities, buyers pay more to have more households of the same ethnicity group. Using the similar set up in Singapore public housing market, Wong (2013) finds an inverted U-shape effect of the ethnicity presence on buyers' willingness to pay controlling for the difference in ethnic amenities. The preference for ethnicity itself cannot explain the convexity in our results; it, however, could amplify the convexity in results after controlling for ethnicity preference.

The second potential factor is the existence of cultural amenities associated with a high fraction of an ethnicity group in a block. Integration of ethnic preference increases the ethnicspecific amenities, which will be more valuable for particular ethnic group. However, the ethnic-based amenities are unlikely to increase exponentially in public housing estates in Singapore. The supply of new amenities, such as schools, supermarkets, clinics, hawker centres, and sports and recreational facilities, are limited by lands available in the housing estates. The ethnic-based amenity supply is unlikely to drive the convexity in the results.

The last factor this paper claims is the ethnic social network, which affects COV premiums through trading behavior in the ethnic social network. The preference matching between buyer and seller is one example of the ethnic social network. The sharing of "taste" in things, such as interior design and social amenities between buyers and sellers of the same ethnicity group can explain the positive COV premiums. A high fraction of the own ethnicity group exponentially increases the chance of matching ethnic preference through the ethnic social network, which could explain the convexity in COV premium. Figure 1 shows positive COV payments in most of the transaction, and the results indicate that transactions are not randomly matched, but selected among those who agree on the value, which may include an ethnic-specific value for the unit. We will further explore the role of ethnicity matching in COV premiums in the next section.

6.3. Robustness: Temporal Variations in COV Premium

Do COV premiums vary over time? We include a triple interactive term comprising the ethnicity variable, the ethnic quota-binding dummy and the year dummy to the specification of Table 4 to capture the year by year variations in COV (psm). The detailed panel regression results are reported in Appendix (Table A2). Based on the coefficients from the regression, we plot the temporal variations of COV premiums (or discounts) associated with the within ethnicity quota in Figure 5. The three panels in Figure 5 represent the three comparable ethnicity quota-year effects sorted by the buyer ethnicity groups.

Panel A reports the differences in COV (psm) that Chinese buyers pay in each ethnicity quota. The black solid line shows the average COV (psm) that Chinese buyers pays in all blocks; the red long-dashed line shows the average COV (psm) that Chinese buyer pays in Chinese quota blocks; and the blue short-dashed line shows the average COV (psm) that Chinese buyer pays in Malay quota blocks; and the green dotted line shows the average COV (psm) that Chinese buyer pays in Indian quota blocks. We find that Chinese buyers consistently pay more for comparable housing units in the Chinese quota blocks (red longdashed line) than the average (black solid line); but consistently pay below the average COV premiums (black solid line) in Malay quota blocks (blue short-dashed line) and in Indian quota (green dotted line) for comparable housing units.

Panel B reports the difference in COV (psm) that Malay buyers pays in each ethnicity quota. Malay buyers pay more COV (psm) than the average in Malay quota-binding blocks, but pay below the average COV psm in Chinese quota-binding blocks. Malay buyers pay more than average for the units in Indian quota for some years, which may be due to the fact that there exist some blocks with both Malay and Indian quotas. Panel C reports the difference in COV (psm) that Indian buyers pays in each ethnicity quota. Indian buyers pay more COV (psm) than the average in Indian quota-binding blocks, but pay below the average COV (psm) in Chinese quota-binding blocks. The results are consistent with the earlier findings.

6.4. Within-Ethnicity Transactions and COV premium

The early results show significant increases in COV premium with a high concentration of the own ethnicity group in a housing block. We argue that the results are not caused by the supply constraints in the ethnic quota-binding conditions. Instead, we find incremental and positive COV premiums in the interaction between buyers' ethnicity and own ethnic quota, but the opposite (negative) effects in the interaction between buyers' ethnicity and other ethnic quota. We argue that the convex relationship cannot be explained by neither the preference for neighbors of the own ethnicity group (inverted U-shape curve as in Wong (2013)) nor the supply of ethnic-based amenities.

We further argue that the results are driven by the ethnic social network, which is related to preference matching between buyers and sellers in the search process. That is, buyers share similar "taste" with sellers of the same ethnicity group in things, such as social amenities and housing attributes. As a result, the ethnic social network increases housing price via matched preference that exists only the within ethnicity group.

To explore the effect of ethnic social network hypothesis, we construct the repeat-sale samples based on housing units sold twice or more times. We find 3,652 units sold twice, 99 units sold for 3 times, and 3 units sold for 4 times in our samples. For each pair of repeated housing transactions, we identify the ethnicity of seller, based on the buyer identity of the same unit in the previous transaction. As a result, we are able to match buyer and seller information for 3,859 repeated transactions, of which 289 are the cross-ethnicity transactions, and 3,570 are the within-ethnicity transactions. Figure 6 shows the histograms of COV (psm) for the within-ethnicity (Panel A) and the cross-ethnicity transactions (Panel B). There is a discernible spike in the frequency at zero COV premium in both histograms. However, we find that the frequency of zero COV transactions are higher in the cross-ethnicity group sample (3.81%) than the within-ethnicity group sample (2.02%). The results indicate that buyers and sellers are more likely to trade at appraisal prices (or at zero COV psm), when they are from different ethnicity groups. The average COV (psm) in the within-ethnicity group transactions estimated at SGD336.15 is higher than the average COV (psm) of SGD292.88 in the cross-ethnicity group transactions. The average COVs are shown by the vertical red dotted line in the histograms. The difference in mean is statistically significant at a 1% level.

Based on the buyer and seller ethnicity identities, we can test the effects of the withinethnicity transaction on COV (psm) between buyers of the same ethnicity group those of the different ethnicity group. Table 7 reports the panel regression results of the within-ethnicity group transactions and the ethnicity quota on COV (psm). The dependent variable is the COV (psm). Panel A reports the results using all buyers in the repeat sale samples. Column (1) includes a dummy variable for the ethnicity quota. LEthnicity Quota equals to 1 for the transactions by buyers in their own ethnic quota binding blocks. The independent variables include size (sqm), floor level, distance to nearest MRT, primary school quality within 1 km radius and within 1-2 km radius. We also include the year fixed effects, the month fixed effects, and the property type fixed effects. We find that the COV (psm) is higher when buyers purchase housing units in blocks with the own ethnicity binding quota. Column (2) includes a dummy variable for the within-ethnicity group transactions, where the Within Ethnicity Transaction equals to 1, if a transaction is made between a buyer and a seller of the same ethnicity type. We find that the within-ethnicity transactions have a higher COV (psm) than the cross-ethnicity transactions. Column (3) includes a dummy variable on the within-ethnicity group transactions and its interaction with the ethnicity quota dummy. A "horse-race" between the two factors is done to identify the dominant factor. We find that the within-ethnicity transactions still show positive premiums on COV (psm) and the effect is stronger in the within-ethnicity quota binding blocks. However, the coefficient on the ethnicity quota dummy is negative, but statistically insignificant.

Panel B reports the results on Chinese buyers. Column (1) reports the result with the Chinese buyer dummy interacted with a dummy for blocks with a binding Chinese quota. The results are similar to those reported in column (1) in Table 4 but using the repeat sale samples. We find significantly higher COV (psm), when Chinese buyers purchase units in Chinese quota binding blocks. Column (2) includes the within-Chinese transaction dummy; and we find significantly positive COV premiums for the within-Chinese group transactions, even after controlling for the buyer ethnicity and the own ethnicity quota. Column (3) includes the within-Chinese transaction dummy and its interaction with the Chinese quota dummy. We find significant COV premiums in the within-Chinese transactions, and the effect is stronger in the Chinese quota binding blocks. Column (4) includes both interactions in (2) and (3) for a "horse-race" between the within-Chinese transaction and the Chinese buyers effects. We find that Chinese buyers in the Chinese quota blocks is not sufficient to generate COV premiums. However, when the seller is also a Chinese, the Chinese quota effect on COV premiums becomes significant.

Panel C reports the results on Malay buyers using the same specification as in Panel B. Column (1) shows that Malay buyers pay COV premiums when they purchase units in Malay quota binding blocks. Column (3) shows that the within-Malay transactions itself show lower COV (psm); but the within-Malay transactions in the Malay quota binding blocks show positive COV premiums. In a horse-race between those two interactions in column (4), both of them become statistically insignificant indicating that Malay buyers in the Malay quota binding blocks is not a sufficient condition to produce COV premiums. Due to limited repeat sales sample for Indian buyers, the comparable analyses are not conducted for the Indian group.¹⁴

Table 8 reports the panel regression results for the within-ethnicity group transactions and the fraction of ethnicity group on COV (psm). Panel A reports the results on Chinese buyers. Column (1) reports the result with the Chinese buyer dummy interacted with the fraction of Chinese in a block. The independent variables include size (sqm), floor level, distance to nearest MRT, primary school quality within 1 km radius, and within 1-2 km radius. We also include the year fixed effects, the month fixed effects, and the property type fixed effects. The results are similar those reported in column (1) in Panel B of Table 5 but using the repeat sale samples. We find significantly higher COV (psm) for Chinese buyers in blocks with a high fraction of Chinese. Column (2) adds the within-Chinese transaction dummy to column (1); and we find significantly positive COV premiums in the within-Chinese transactions after controlling for the effects of Chinese buyers and the Chinese fraction in the block. Column (3) includes the within-Chinese transaction dummy and its interaction with the fraction of Chinese. We find significant COV premium in the within-Chinese transactions, when the fraction of Chinese increases. Column (4) includes both interactions in (2) and (3) for a horse-race between the within-Chinese transaction and the Chinese buyer effects. We find that Chinse buyer in a block with a high fraction of Chinese is not a condition that is strong enough to generate COV premium. However, when the seller is also a Chinese, we find a positive relationship between COV premiums and Chinese fraction in a block.

Panel B reports the results on Malay buyers using the same specification as in Panel A. We find positive COV premiums that are associated with Malay buyer in blocks with a high fraction of Malay. When a horse-race between the two interactions is done, Malay buyer in blocks with a high fraction of Malay is a sufficient condition to produce COV premiums, which is different from the results for the other ethnicity groups. Panel C reports the results on Indian buyers using with same specification. Despite having only a small sample of Indian

 $^{^{14}}$ Our repeated sale samples consist only of 15 transactions in the blocks with an Indian quota.

buyers (5%), we find that Indian buyer in blocks with a high fraction of Indian is not a sufficient condition to generate COV premiums. When the seller is also an Indian, we find that COV premiums are positively correlated with increases in the fraction of Indian.

Table 7 and Table 8 show positive and economically significant COV premiums with the high ethnicity presence only if both buyers' and sellers' ethnicity types are matched. The results are robust and consistent in models using both a discrete measure of the ethnicity quota, and a continuous fraction measure of the block-level ethnicity group. The importance of the within-ethnicity transaction supports the ethnic social network hypothesis via matching ethnic preference.

6.5. Ethnic Social Network: Evidence in Transaction Volume

We have investigated the ethnic social network effects using the COV premiums as a pricing mechanism. We further explore the ethnic social network effects using the transaction volume mechanism in this section. The ethnic preference matching hypothesis predicts 1) a high COV premium in the within-ethnicity transactions; and also 2) a high concentration of the within ethnicity transactions. That is, the matching of the ethnic-specific taste should increase the propensity of buyer and seller of the same ethnicity group to trade; and higher COV premiums in the transaction should reflect the ethnic-specific values.

Figure 7 shows the distributions of ethnicity matching between buyers and seller in the repeat sale samples. Panel A shows the number of transactions by the buyers' and sellers' ethnicity; and Panel B shows the fraction of transactions within the buyer ethnicity groups. The first figures in both Panels show the ethnicity matching in all blocks. For buyers of each ethnicity group, the numbers of transactions with Chinese, Malay, Indian, and Others are shown. We find a high concentration of the within ethnicity transactions. 94.2% of the Chinese buyers (2583 out of 2741) purchase units from Chinese sellers, 1.3% (37 out of 2741) from Indian sellers, and 3.7% (101 out of 2741) from Malay sellers. 83.6% of the Indian buyers (188 out of 225) purchase units from Indian sellers, 8% (18 out of 225) from Chinese sellers,

and 4% (9 out of 225) from Malay sellers. 91.7% of the Malay buyers (778 out of 848) purchase units from Malay sellers, 6.7% (57 out of 848) from Chinese sellers, and 1.4% (12 out of 848) from Indian buyers.

We decompose the matching frequency between buyers and sellers in the ethnicity quota binding blocks. In the Chinese quota blocks (top right-hand figures in both panels), 98% of the Chinese buyers purchase units from Chinese sellers, 0.7% from Indian sellers, and 0.9% from Malay sellers. It is as expected to have a high concentration of Chinese transactions in Chinese quota binding blocks. Combined with the early findings of the positive COV premiums in the within-ethnicity transactions in own ethnicity quota blocks, this evidence supports the ethnic social network effects via the preference matching channel.

The same prediction, however, arises from the ethnic social network hypothesis through information spillover channel. The evidence on COV premium and concentration of transactions within ethnicity is also likely to happen through information spillover channel, which happens among people speaking same language and/or with same education background (Bertrand et al. (2000)). That is, if the ethnic-specific information flows through the network, it will be empirically inseparable between two channels, at least based on our data. Then what we find will be just a special case of the information spillovers story within ethnicity but not the effect of ethnic social network.

Interestingly, we find the same concentration in the other ethnicity buyers in Chinese quota binding blocks. In Chinese quota binding blocks, 81% of the Indian buyers purchase units from Indian sellers, 8.6% from Chinese sellers, and 3.4% from Malay sellers. Similarly, 90.1% of the Malay buyers purchase units from Malay sellers, 6.2% from Chinese sellers, and 3.7% from Indian sellers. Why do Malays trade with other Malays only and Indians trade with other Indians only in Chinese quota binding blocks that have more Chinese amenities? Given that Indian buyers and Malay buyers pay COV discounts for the within-ethnicity transactions in Chinese quota binding blocks, the high within ethnicity transaction volumes do not fit the preference matching and/or information spillovers stories; however, they support the

pure ethnic social network effects after controlling for preference matching and information spillovers. We find similar concentrations in Malay and Indian quota binding blocks.

The pure ethnic social network effect, which is orthogonal to information spillover, should predict 1) increases in the intensity of transactions within the ethnicity group; but 2) no COV premium associated with the within ethnicity transaction since no information spillover and/or no matched preference are generated in the transactions. For example, if buyers and sellers from the same ethnicity group use real estate agents of the same ethnicity group, we expect the increase in the intensity of the within-ethnicity transactions without increasing the COV premiums.¹⁵ Buyers and sellers may still be more comfortable to communicate in their own native languages in housing transactions, despite the fact that English is a prevalent business language spoken in Singapore's society. Efficient communication facilitates negotiations between buyers and sellers of the same ethnicity group relative to those from different ethnicity groups. The existence of pure ethnic social network implies that the search friction in the housing market is one possible factor contributing to the racial segregation in the housing market.

7. Conclusion

This paper investigates the ethnic social network in Singapore's resale public housing market. Based on a unique dataset containing information on Cash-Over-Valuation (COV) for 73,107 resale public housing transactions from 2007 to 2012, we find that COV per square meter (psm), which measures the differences between transaction prices and appraisal values, significantly increases with the presence of buyers' own ethnic group in housing blocks. The results coincide with the view that buyers value cultural amenities in housing blocks with a high concentration of residents of the same ethnicity group.

However, we also find a strong convexity in COV premiums with respect to the ethnicity

¹⁵They may use ethnic-specific real estate web-portal or real estate agents to facilitate transactions within the ethnicity group.

presence, which can not be fully explained by ethnic-based factors, such as cultural amenities, preference on the own ethnicity group, and supply constraints. Using repeat sale samples, we find that preference matching between buyers and sellers through the ethnic social network is a key condition for the convex COV premiums. In other words, the value of cultural amenities are embedded into transaction price, only if buyers and sellers share common preferences.

Lastly, we find an extremely high concentration of transactions within the ethnicity groups. The results are found not only in the own-ethnicity concentrated blocks, but also in otherethnicity concentrated blocks. The results support the ethnic social network hypothesis, which predicts a higher transaction volume in the within ethnicity group than in the cross ethnicity group. A high concentration of the within ethnicity group in blocks without having common preferences, i.e. blocks with quota on other ethnicity group, indicates the importance of the pure ethnic social network in housing market; and the existence of such network could cause disconnection and aggravate segregation in housing markets.

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Table 1: Population Composition of Singapore and the Ethnic Integration Policy

We report the population composition of Singapore in 1989 and 2010 and the maximum ethnic limits imposed by the Ethnic Integration Policy. From March 1989, the Ethnic Integration Policy imposed maximum ethnic limits in neighborhoods and blocks in Singapore. In March 2010, the limit for Indian group has been increased from 10% to 12% for neighborhoods and from 13% to 15% for blocks.

	Population	n Composition	Maximum Ethnic Limits						
	1989	2010	From 1 March 1989		From 5 Marc	h 2010			
Ethnic Group			Neighborhood	Block	Neighborhood	Block			
Chinese	77.80%	74.10%	84.00%	87.00%	84.00%	87.00%			
Malays	14.20%	13.40%	22.00%	25.00%	22.00%	25.00%			
Indians	7.00%	9.20%	10.00%	13.00%	12.00%	15.00%			

Table 2: Summary Statistics

We construct our data by merging the public housing resale transaction data from Singapore Real Estate Exchange to a proprietary big database on Singapore residents. Our sample period is from 2007 to 2012. Panel A reports the composition of buyers in our data. There are four groups of buyers identified: Chinese buyer, Malay buyer, Indian buyer, and Other buyers. Panel B reports the summary statistics of variables we use in our analysis. Appraisal Value is an appraisal of a house from a panel of accredited appraisals, which is similar to the standard hedonic models. Appraisal Value (psm) is the Appraisal Price per square meter. COV is the cash over valuation, which is the difference between the final agreed price and the appraisal value. COV (psm) is the COV per square meter. Unit floor is the floor level of a house. Size (sqm) is the size of a house. Distance to Nearest MRT is the linear distance of a house to the nearest mass rapid transit (MRT) station. Primary School Quality within 1 km radius is the average school quality around 1 km radius from a house, based on the Primary School Leaving Examination results. Primary School Quality within 1-2 km radius from a house. Panel C reports the type of property in our data. There are 8 types of properties: 1 Rooms, 2 Rooms, 3 Rooms, 4 Rooms, 5 Rooms, HUDC, Jumbo, and Executive. For the robustness of the empirical analyses, we winsorize Appraisal Value and COV at the 1% level on both tails.

Panel A: Buyer Composition					
	Chinese	Malay	Indian	Others	Total
	$53,229 \\72.81\%$	$\frac{15,\!184}{20.77\%}$	$3,\!801 \\ 5.2\%$	$893 \\ 1.22\%$	$73,\!107\ 100\%$
Panel B: Summary Statistics					
	Obs	Mean	Std. Dev.	Min	Max
Appraisal Value	73,107	382,406	117,557	169,000	750,000
Appraisal Value (psm)	73,107	3,927.30	973.87	1,198.63	11,538.46
COV	73,107	24,136	18,840	-22,000	90,000
COV (psm)	73,107	253.47	191.84	-550.00	1,538.46
Unit Floor	73,107	7.55	4.80	1.00	40.00
Size (sqm)	$73,\!107$	99.00	25.19	31.00	243.00
Distance to Nearest MRT	$73,\!107$	0.89	0.55	0.04	3.52
Primary School Quality within 1 km radius	$71,\!057$	-0.10	0.60	-0.85	3.66
Primary School Quality within 1-2 km radius	72,208	-0.11	0.42	-0.85	3.54
Devised C. Devise series There is					
Panel C: Property Type	1 Rooms	2 Rooms	3 Rooms	4 Rooms	-
	137	433	19,356	27,085	
	0.19%	0.59%	26.48%	37.05%	
	5 Rooms	HUDC	Jumbo	Executive	-
	19,291	42	38	6,725	
	26.39%	0.06%	0.05%	9.20%	

Table 3: Ethnicity Presence in Blocks

In Panel A, we report the summary statistics of ethnicity presence in blocks. In Singapore, the postal-code system assigns a unique 6 digit postal code for each housing block and we have 8194 blocks in our sample. We report summary statistics of the fraction of Chinese, Malay, and Indian residents in each block. Panel B reports the determinants of the ethnicity fractions in blocks. In columns (1)-(3), we report the linear regression results of various determinants on the ethnicity fraction. In column (1), we use the fraction of Chinese residents in a block as a dependent variable. Independent variables include Distance to nearest MRT, Primary School Quality within 1 km radius, Primary School Quality within 1-2 km radius, Average Unit Size (sqm) in a Block, and Maximum Building Floor. In column (2), we use the fraction of Malay residents in a block as a dependent variable. In column (3), we use the fraction of Indian residents in a block as a dependent variable. In Columns (4)-(6), we report the logit regression results of various determinants on the ethnicity quota. As reported in Table 1, Chinese ethnicity quota binds if a block has more than 25% Malay residents, and Indian ethnicity quota binds if a block has more than 25% Malay residents, and Indian ethnicity quota binds if a block has more than 13% or 15%. In column (4), we use the Chinese quota as a dependent variable. In column (5), we use the Indian quota as a dependent variable. The table reports point estimates with heteroskedasticity robust t-statistics in parentheses. ***, **, ** denotes 1%, 5%, and 10% statistical significance.

	Obs	Mean	Std. Dev.	p10	p25	p50	p75	p90
Fraction of Chinese	8,194	79.95	9.84	66.99	73.33	81.38	87.56	91.03
Fraction of Malay	8,194	15.13	9.57	3.76	7.44	13.89	21.92	27.82
Fraction of Indian	8,194	3.82	2.96	0.86	1.87	3.33	5.13	7.12
Panel B: Determinants	of Ethnicity Presence	e in Blocks						
	v	(1)	(2)	(3)		(4)	(5)	(6)
		Fraction of	Fraction of	Fraction of		Chinese	Malay	Indian
Variables		Chinese	Malay	Indian		Quota	Quota	Quota
Distance to nearest MRT	٦	-2.846***	3.103***	-0.223***		-0.858***	0.489***	0.0622
		(-15.51)	(17.67)	(-3.735)		(-14.56)	(8.444)	(0.240)
Primary School Quality	within 1km radius	1.575***	-1.762***	0.0826		0.294***	-0.420***	-0.458*
		(9.883)	(-11.03)	(1.529)		(6.668)	(-6.928)	(-1.889)
Primary School Quality	within 1-2km radius	2.597^{***}	-2.495^{***}	-0.170**		0.454^{***}	-0.638***	-1.424***
		(10.21)	(-10.22)	(-2.409)		(7.116)	(-6.744)	(-3.424)
Average Unit Size (sqm)	in a Block	-0.0219^{***}	-0.00331	0.0198^{***}		-0.00525***	-3.80e-05	0.0156^{***}
		(-4.629)	(-0.726)	(9.699)		(-4.709)	(-0.0310)	(4.282)
Maximum Building Floor	r	0.593^{***}	-0.508***	-0.0745^{***}		0.0839^{***}	-0.141***	-0.401***
		(25.47)	(-22.77)	(-8.549)		(15.64)	(-19.30)	(-11.59)
Constant		78.11^{***}	18.35^{***}	2.818^{***}		-0.672^{***}	-0.672^{***}	-3.498***
		(136.8)	(33.11)	(14.45)		(-5.262)	(-4.525)	(-6.732)
Observations		7,864	7,864	7,864		7,864	7,864	7,864
R-squared		0.134	0.115	0.043				

Table 4: COV and the Blocks with Ethnicity Quota

We report the panel regressions of buyer's ethnicity and the presence of same ethnicity group in the block (discrete measure) on COV per square meter (COVpsm). The dependent variable is COVpsm, winsorized at 1% level. Column (1) includes a dummy variable for Chinese buyer (I_Buyer Ethnicity) and an interaction of the Chinese buyer dummy with dummies for ethnicity quota on the block. I_Chinese Quota equals 1 if the block has binding Chinese quota and equals 0 otherwise. I_Malay Quota equals 1 if the block has binding Chinese quota and equals 0 otherwise. I_Malay Quota equals 1 if the block has binding Chinese quota and equals 0 otherwise. I_Malay Quota equals 1 if the block has binding Chinese quota and equals 0 otherwise. I.Indian Quota equals 1 if the block has binding Chinese quota and equals 0 otherwise. Isomoth fixed effects, block fixed effects, and property type fixed effects. Since we have block level fixed effect, we cannot identify the effect of ethnicity quota itself but we still can identify the interaction. Column (2) is about Malay buyer and column (3) is about Indian buyer with same setup as in column (1). The table reports point estimates with heteroskedasticity robust t-statistics in parentheses. ***, **, * denotes 1%, 5%, and 10% statistical significance.

	Dependent Variable: COVpsm					
	(1)	(2)	(3)			
Variables	Chinese Buyer	Malay Buyer	Indian Buyer			
I_Buyer Ethnicity	42.43***	-46.54^{***}	-11.50***			
	(25.65)	(-25.88)	(-3.669)			
I_Buyer Ethnicity \times I_Chinese Quota	44.20***	-46.18^{***}	-57.34^{***}			
	(11.03)	(-9.577)	(-8.449)			
I_Buyer Ethnicity \times I_Malay Quota	-11.30***	14.86^{***}	8.086			
	(-3.859)	(4.894)	(1.265)			
I_Buyer Ethnicity \times I_Indian Quota	-36.48*	32.31	1.693			
	(-1.958)	(1.586)	(0.0711)			
I_Indian Quota	-5.425	-37.73	-27.72			
	(-0.195)	(-1.439)	(-1.080)			
Size (sqm)	-0.644***	-0.649***	-0.603***			
	(-4.826)	(-4.864)	(-4.499)			
Unit Floor	7.470^{***}	7.593^{***}	8.497***			
	(48.20)	(49.06)	(55.98)			
Observations	73,107	73,107	73,107			
R-squared	0.486	0.485	0.477			
Block FE	Yes	Yes	Yes			
Year, Month FE	Yes	Yes	Yes			
Property Type FE	Yes	Yes	Yes			

Table 5: COV and the Fraction of Ethnicity Presence

We report the panel regressions of buyer's ethnicity and the presence of same ethnicity group in the block (continuous measure) on COV per square meter (COVpsm). The dependent variable is COVpsm, winsorized at 1% level. Panel A reports the results with block fixed effects. Columns (1)-(3) include a dummy variable for Chinese buyer (LBuyer Ethnicity) and an interaction of the Chinese buyer dummy with the fractions of Chinese, Malay and Indian in the block. In column (1), we interact Chinese buyer dummy with the fraction of Chinese in each block. Independent variables include Size (sqm) and Unit Floor. We also include year fixed effects, month fixed effects, block fixed effects, and property type fixed effects. Since we have block level fixed effect, we cannot identify the effect of ethnicity fraction itself but we still can identify the interaction. In column (2), we interact Chinese buyer dummy with the fraction of Maly residents in each block. In column (3), we interact Chinese buyer dummy with the fraction of Indian residents in each block. Columns (4)-(6) use Malay buyer dummy and Columns (7)-(9) use Indian buyer dummy. Panel B reports the results without block fixed effects. Specifications are similar to Panel A except block fixed effects and additional independent variables such as Distance to nearest MRT, Primary School Quality within 1 km radius, Primary School Quality within 1-2 km radius. The table reports point estimates with heteroskedasticity robust t-statistics in parentheses. ***, **, * denotes 1%, 5%, and 10% statistical significance.

Panel A: With Block Fixed Effects									
				Depende	nt Variable:	COVpsm			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	(Chinese Buy	er		Malay Buye	r		Indian Buye	r
I_Buyer Ethnicity	-114.8***	83.48***	54.38***	114.6***	-90.39***	-54.50***	173.0***	-64.62***	-26.75***
· ·	(-10.14)	(25.80)	(22.57)	(9.385)	(-23.96)	(-21.30)	(8.027)	(-11.76)	(-5.032)
I_Buyer Ethnicity \times Fraction of Chinese	2.091***	· · · ·		-2.137***	× /	× /	-2.490***		
	(14.10)			(-13.19)			(-8.993)		
I_Buyer Ethnicity \times Fraction of Malay	· · /	-2.049***			2.200***		× /	2.682***	
		(-13.33)			(12.83)			(9.252)	
I_Buyer Ethnicity \times Fraction of Indian		~ /	-1.911***		· · · ·	1.704^{***}			0.587
· ·			(-3.640)			(2.967)			(0.595)
Size (sqm)	-0.632***	-0.638***	-0.633***	-0.640***	-0.646***	-0.639***	-0.597***	-0.597***	-0.595***
	(-4.741)	(-4.774)	(-4.730)	(-4.800)	(-4.841)	(-4.784)	(-4.450)	(-4.453)	(-4.428)
Unit Floor	7.415***	7.432***	7.476***	7.550***	7.561***	7.624***	8.484***	8.483***	8.512***
	(47.79)	(47.91)	(48.13)	(48.73)	(48.82)	(49.20)	(55.88)	(55.88)	(56.04)
Observations	73,107	73,107	73,107	73,107	73,107	$73,\!107$	73,107	$73,\!107$	$73,\!107$
R-squared	0.486	0.486	0.485	0.485	0.485	0.484	0.477	0.477	0.476
Block FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year, Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5 Continues

Panel B: Without Block Fixed Effects									
	(1)	(0)	(\mathbf{a})	-	nt Variable:	-		(0)	(0)
Variables	(1)	(2) Chinese Buye	(3)	(4)	(5) Malay Buye	(6)	(7)	(8) Indian Buye	(9)
variables	(Junese Duye	er		Malay Duye	ſ		indian buye	ľ
I_Buyer Ethnicity	-126.2***	89.74***	57.66***	129.0***	-97.81***	-54.57***	163.8***	-63.24***	-37.05***
0	(-11.67)	(29.19)	(23.90)	(11.20)	(-27.93)	(-21.82)	(7.602)	(-11.75)	(-6.913)
I_Buyer Ethnicity \times Fraction of Chinese	2.263***	· · · ·	()	-2.346***	× /	· · · ·	-2.403***	· · · ·	× /
v v	(16.04)			(-15.42)			(-8.723)		
I_Buyer Ethnicity \times Fraction of Malay	× ,	-2.291***		· · · ·	2.530^{***}		· · · ·	2.295^{***}	
		(-15.73)			(15.90)			(8.032)	
I_Buyer Ethnicity \times Fraction of Indian		· · · ·	-0.755		· · · ·	-0.708		× ,	2.414^{**}
v v			(-1.391)			(-1.240)			(2.338)
Fraction of Chinese	-0.0422			2.045***		× /	2.120***		× /
	(-0.363)			(25.58)			(29.69)		
Fraction of Malay	· · · ·	0.0286		· · · ·	-2.069***		· · · ·	-2.168***	
v		(0.237)			(-25.28)			(-29.59)	
Fraction of Indian			-0.0973			-1.069***		· · · ·	-0.780***
			(-0.218)			(-3.521)			(-2.841)
Distance to nearest MRT	-28.34^{***}	-28.05***	-32.04***	-28.40***	-28.21***	-32.17***	-29.84***	-29.36***	-34.32***
	(-25.72)	(-25.41)	(-28.86)	(-25.75)	(-25.55)	(-28.99)	(-26.97)	(-26.48)	(-30.74)
Primary School Quality within 1km radius	13.17***	12.95***	15.32***	12.98***	12.82***	15.10***	13.46***	13.20***	16.28***
	(11.71)	(11.51)	(13.63)	(11.50)	(11.35)	(13.40)	(11.83)	(11.59)	(14.32)
Primary School Quality within 1-2km radius	8.294***	8.351***	11.25***	7.978***	8.138***	10.94***	8.220***	8.303***	12.13***
	(4.734)	(4.774)	(6.447)	(4.538)	(4.637)	(6.248)	(4.636)	(4.689)	(6.864)
Size (sqm)	-0.330***	-0.377***	-0.609***	-0.337***	-0.396***	-0.591^{***}	-0.295***	-0.349***	-0.681***
	(-4.178)	(-4.800)	(-7.760)	(-4.267)	(-5.063)	(-7.538)	(-3.702)	(-4.398)	(-8.590)
Unit Floor	7.015***	7.049***	7.430***	7.154***	7.208***	7.561***	8.002***	8.020***	8.636***
	(47.00)	(47.31)	(49.61)	(48.04)	(48.50)	(50.61)	(54.94)	(55.14)	(59.46)
Observations	70,197	70,197	70,197	70,197	70,197	70,197	70,197	70,197	70,197
R-squared	0.355	0.355	0.348	0.353	0.353	0.347	0.343	0.343	0.334
Block FE	No	No	No	No	No	No	No	No	No
Year, Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: COV and the Convexity with the Fraction of Ethnicity Presence

We report the panel regressions of buyer's ethnicity and the presence of same ethnicity group in the block (continuous measure) and its square term on COV per square meter (COVpsm). Dependent variable is COVpsm, winsorized at 1% level. Columns (1)-(3) report results with block fixed effects. Column (1) includes a dummy variable for Chinese buyer (LBuyer Ethnicity) and interactions of the Chinese buyer dummy with the fraction of Chinese and its square term. Independent variables include Size (sqm) and Unit Floor. We also include year fixed effects, month fixed effects, block fixed effects, and property type fixed effects. Since we have block level fixed effect, we cannot identify the effect of ethnicity fraction and its square term but we still can identify the interactions. Column (2) is about Malay buyer and column (3) is about Indian buyer. Columns (4)-(6) report results without block fixed effects. Specifications are similar to columns (1)-(3) except block fixed effects and additional independent variables such as Distance to nearest MRT, Primary School Quality within 1 km radius, Primary School Quality within 1-2 km radius. The table reports point estimates with heteroskedasticity robust t-statistics in parentheses. ***, **, * denotes 1%, 5%, and 10% statistical significance.

(1) Chinese Buyer 291.4*** (3 936)	(2) Malay Buyer -99.43***	(3) Indian Buyer	(4) Chinese Buyer	(5) Malay Buyer	(6) Indian Buyer
291.4***		Indian Buyer	Chinese Buyer	Malay Buyer	Indian Buver
	00 /3***				
		-47.37***	270.6***	-101.3***	-59.85***
					(-10.04)
					(-10.04) 10.75^{***}
					(8.978)
	()			· · · · ·	(8.978) 0.731^{***}
(0.399)	(0.874)	(10.22)	· /		(11.09) -3.746***
				(/	(-4.173)
					-0.281***
					(-2.993)
					-33.95***
					(-30.39)
					16.05***
					(14.15)
					12.18^{***}
			(/	· /	(6.900)
					-0.668***
					(-8.302)
					8.428***
(47.89)	(48.50)	(54.15)	(47.11)	(48.23)	(57.18)
73.107	73.107	73.107	70.197	70,197	70,197
,	,	· · · · · · · · · · · · · · · · · · ·	'	,	0.338
					No
					Yes
					Yes
	$\begin{array}{c} (3.936) \\ -8.719^{***} \\ (-4.404) \\ 0.0709^{***} \\ (5.399) \end{array}$ $\begin{array}{c} -0.635^{***} \\ (-4.772) \\ 7.428^{***} \\ (47.89) \\ \hline 73,107 \\ 0.487 \\ Yes \\ Yes \\ Yes \\ Yes \\ Yes \end{array}$	$\begin{array}{ccccc} -8.719^{***} & 3.326^{***} \\ (-4.404) & (13.73) \\ 0.0709^{***} & 0.0318^{***} \\ (5.399) & (6.874) \end{array}$ $\begin{array}{ccccc} -0.646^{***} \\ (-4.772) & (-4.841) \\ 7.428^{***} & 7.521^{***} \\ (47.89) & (48.50) \end{array}$ $\begin{array}{cccccc} 73,107 \\ 0.487 & 0.485 \\ Yes & Yes \\ Yes & Yes \\ Yes & Yes \end{array}$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$

Table 7: Effects of Within-Ethnicity Group Transactions and Ethnicity Quota

We report the panel regression of within-ethnicity group transactions and ethnicity quota on COV per square meter (COVpsm). The dependent variable is COVpsm, winsorized at 1% level. Panel A reports the results using all buyers in the repeated sale subsample. Column (1) includes a dummy variable for ethnicity quota. I_Ethnicity Quota equals to 1 for the transactions by buyers in blocks with their own ethnic quota. Independent variables include Size (sqm), Unit Floor, Distance to nearest MRT, Primary School Quality within 1 km radius, and Primary School Quality within 1-2 km radius. We also include year fixed effects, month fixed effects, and property type fixed effects. For simplicity, we do not report the coefficients on control variables. Column (2) includes a dummy variable for within-ethnicity group transactions. Within Ethnicity Transaction equals to 1 if the transaction is done between same ethnicity buyer and seller. Column (3) includes a dummy variable within-ethnicity group transactions and its interaction with the dummy for the ethnicity quota. Panel B reports the results on Chinese buyers. Column (1) reports the result with Chinese buyer dummy interacted with a dummy for Chinese quota. Column (2) additionally includes within-Chinese transaction dummy to column (1). Column (3) includes within-Chinese transaction dummy and its interaction with a dummy for Chinese quota without having the interaction between Chinese quota dummy and Chinese buyer dummy. Column (4) includes both interactions in (2) and (3). Panel C reports the results on Malay buyers. Specifications are same as in Panel B. The table reports point estimates with heteroskedasticity robust t-statistics in parentheses. ***, **, * denotes 1%, 5%, and 10% statistical significance.

Panel A: All Buyers	(1)	(2)	(3)	
	De	pendent Var	iable: COV	osm
I_Ethnicity Quota	30.36***		-26.01	
L'Ennienty Quota	(4.683)		(-0.921)	
Within Ethnicity Transaction	(4.005)	29.99***	(-0.521) 19.18*	
		(3.132)	(1.870)	
Within Ethnicity Transaction \times LEthnicity Quota	a.	(0.102)	57.36**	
			(1.978)	
Panel B: Chinese Buyers	(1)	(2)	(3)	(4)
I aner D. Onniese Duyers		pendent Var	· · /	
	De	pendent var		
L-Chinese Quota	-11.19	-10.81	-12.61	-10.78
	(-0.789)	(-0.762)	(-0.956)	(-0.759)
I_Chinese Buyer	44.63***	-4.217	0.318	2.213
	(7.189)	(-0.333)	(0.0256)	(0.165)
I_Chinese Buyer \times I_Chinese Quota	53.55^{***}	50.95^{***}		-20.01
	(3.285)	(3.127)		(-0.605)
I_Within Chinese Transaction		53.38^{***}	48.11^{***}	46.47^{***}
		(4.338)	(3.879)	(3.531)
I_Within Chinese Transaction \times I_Chinese Quota			54.62***	72.79**
			(3.524)	(2.355)
Panel C: Malay Buyers	(1)	(2)	(3)	(4)
Taner C. Maray Dayors		pendent Var		
	De	pendent var		,5111
I_Malay Quota	-47.41***	-47.49***	-46.26***	-47.48***
· -	(-6.216)	(-6.227)	(-6.148)	(-6.225)
I_Malay Buyer	-64.06***	-31.88	-17.36	-26.30
	(-8.258)		(-0.870)	(-1.132)
I_Malay Buyer \times I_Malay Quota	59.02***	60.18***		37.17
	(4.620)	(4.705)		(0.842)
I ₋ Within Malay Transaction		-35.71^{*}	-50.64^{**}	-41.91^{*}
		(-1.747)	(-2.406)	(-1.740)
I_Within Malay Transaction \times I_Malay Quota	_		60.75***	24.80
45	5		(4.686)	(0.553)

Table 8: Effects of Within-Ethnicity Group Transactions and Ethnicity Fraction

We report the panel regression of within-ethnicity group transactions and the fraction of ethnicity group on COV per square meter (COVpsm). The dependent variable is COVpsm, winsorized at 1% level. Panel A reports the results on Chinese buyers. Column (1) reports the result with Chinese buyer dummy interacted with the fraction of Chinese in a block. Independent variables include Size (sqm), Unit Floor, Distance to nearest MRT, Primary School Quality within 1 km radius, and Primary School Quality within 1-2 km radius. We also include buyer ethnicity fixed effects, year fixed effects, month fixed effects, and property type fixed effects. For simplicity, we do not report the coefficients on control variables. Column (2) additionally includes within-Chinese transaction dummy to column (1). Column (3) includes within-Chinese transaction dummy and its interaction with the fraction of Chinese without having the interaction between the fraction of Chinese and Chinese buyer dummy. Column (4) includes both interactions in (2) and (3). Panel B reports the results on Malay buyers and Panel C reports the results on Indian buyers. Specifications are same as in Panel A. The table reports point estimates with heteroskedasticity robust t-statistics in parentheses. ***, **, * denotes 1%, 5%, and 10% statistical significance.

Panel A: Chinese Buyers	(1)	(2)	(3)	(4)
	De	pendent Var	iable: COV	osm
I_Chinese Buyer	-193.8***	-229.6***	0.554	18.04
Lenniese Buyer	(-4.443)	(-5.135)	(0.0445)	(0.148)
Fraction of Chinese	-0.363	-0.352	-0.378	-0.357
	(-0.812)	(-0.786)	(-0.878)	(-0.796)
I_{-} Chinese Buyer × Fraction of Chinese	3.165***	3.032***	(0.010)	-0.230
L'emiliese Dayer // Traction of emiliese	(5.521)	(5.298)		(-0.146)
L-Within Chinese Transaction	(0.021)	50.08***	-196.3***	-212.1*
		(4.050)	(-4.297)	(-1.750)
I_Within Chinese Transaction \times Fraction of Chinese		(1.000)	3.236***	3.445^{**}
			(5.714)	(2.210)
			(0.111)	(2:210)
Panel B: Malay Buyers	(1)	(2)	(3)	(4)
		pendent Var		
L_Malay Buyer	-109.9***	-77.65***	-12.68	-81.23
	(-7.222)	(-3.225)	(-0.624)	(-1.593)
Fraction of Malay	-2.712***	-2.718***	-2.616***	-2.718^{***}
	(-7.396)	(-7.412)	(-7.222)	(-7.411)
$I_Malay Buyer \times Fraction of Malay$	3.400^{***}	3.466^{***}		3.655^{*}
	(5.173)	(5.281)		(1.653)
I_Within Malay Transaction		-36.82^{*}	-99.82***	-32.86
		(-1.811)	(-3.892)	(-0.627)
I_Within Malay Transaction \times Fraction of Malay			3.346^{***}	-0.209
			(5.022)	(-0.0925)
Panel C: Indian Buyers	(1)	(2)	(3)	(4)
	De	pendent Var	iable: COV	psm
I_Indian Buyer	-16.24	8.538	-4.240	100.1**
1_indian Duyer	(-0.734)	(0.283)	(-0.163)	(2.493)
Fraction of Indian	(-0.734) -0.232	(0.283) -0.240	(-0.103) -0.658	(2.495) -0.229
Tachon OI IIIUIAII	(-0.252)	(-0.240)	(-0.038)	(-0.143)
I.Indian Buyer \times Fraction of Indian	(-0.145) -3.418	(-0.150) -3.116	(-0.409)	(-0.143) -24.99^{***}
Lindian Duyer × Fraction of Indian	(-0.727)	(-0.646)		(-3.706)
I-Within Indian Transaction	(-0.121)	(-0.040) -31.39	-42.51	(-3.700) -145.4^{***}
		(-1.140)	(-1.267)	(-3.250)
I. Within Indian Transaction \times Fraction of Indian		(-1.140)	(-1.207) 1.989	(-3.250) 26.57^{***}
$1_{\text{within indian fransaction } \times \text{Fraction of indian}}{46}$				
40			(0.442)	(3.411)

Figure 1: Histogram of COV (psm)

The figure shows the histogram of COV (psm) of our data from 2007 to 2012. COV is the cash over valuation, which is the difference between the final agreed price and the appraisal value. COV (psm) is the COV per square meter. Average COV (psm) is reported with red-dot line.

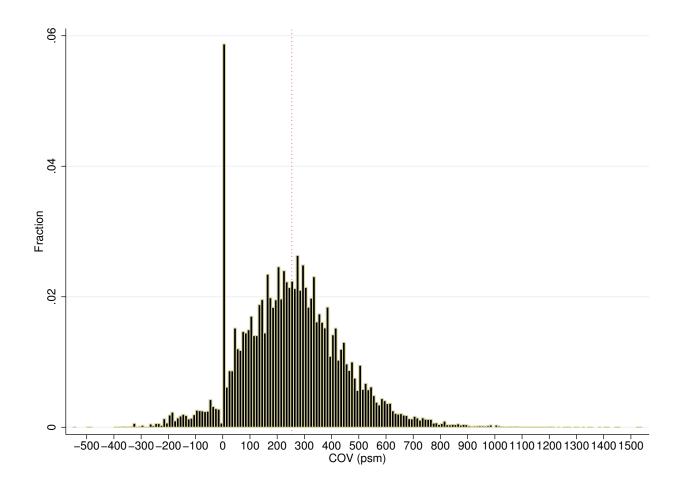


Figure 2: Time Series Variation in COV

The figure shows the time trend of average COV (psm) and the ratio of COV to total transaction price during the sample period. Average COV (psm) is reported in blue-dash line with the scale on the left. The ratio of COV to total transaction price is reported in red-solid line with the scale on the right.

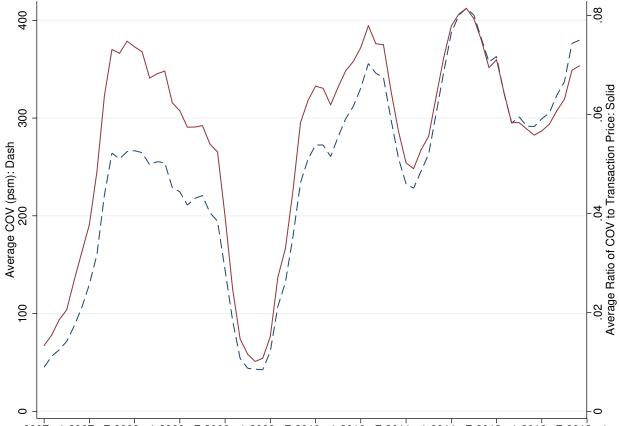




Figure 3: Compositions of Singapore's Resident Populations (1980-2016)

The figure shows the composition of Singapore's resident population from 1980 to 2016. The fractions of Chinese, Malay, and Indian are reported. The data is from the Department of Statistics Singapore.

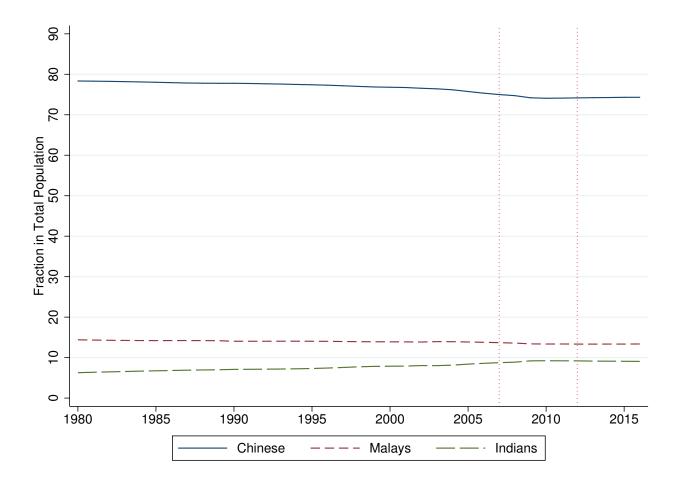


Figure 4: Convexity in COV with the Fraction of Ethnicity

The figure shows the convexity in COV associated with the fraction of ethnicity group. Panel A reports the average COV (psm) paid by Chinese, Malay, and Indian by the fraction of Chinese. We include the locally weighted smoothed fit (lowess) for the scatter plot. Panel B reports the average COV (psm) paid by Chinese, Malay, and Indian by the fraction of Malay. Panel C reports the average COV (psm) paid by Chinese, Malay, and Indian by the fraction of Indian.

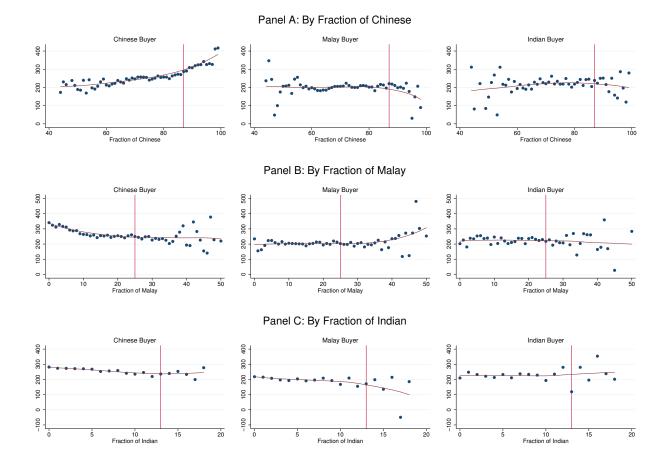


Figure 5: Time Series Variations in COV with Ethnicity Quota

The figure shows the difference in COV (psm) for ethnicity quota by year. We expand Table 4 for the estimates and they are reported in Appendix Table 2. Panel A reports the differences in COV (psm) that Chinese buyer pays in each ethnicity quota. Black solid line shows the average COV (psm) that Chinese buyers pays in all blocks. Red long-dash line shows the average COV (psm) that Chinese buyer pays in Chinese quota blocks. Blue short-dash line shows the average COV (psm) that Chinese buyer pays in Malay quota blocks. Green dot line shows the average COV (psm) that Chinese buyer pays in Malay quota blocks. Green dot line shows the average COV (psm) that Chinese buyer pays in Indian quota blocks. Panel B reports the difference in COV (psm) that Malay buyers pays in each ethnicity quota. Panel C reports the difference in COV (psm) that Indian buyers pays in each ethnicity quota.

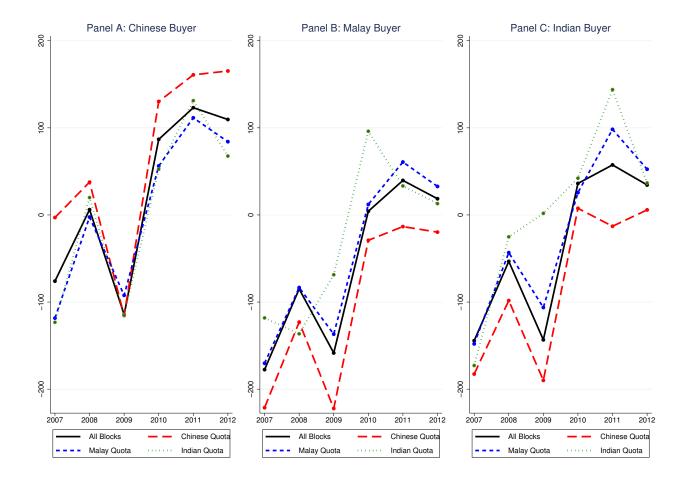


Figure 6: Histogram of COV (psm): Within- vs Cross- Ethnicity Transactions

The figure shows the distributions of COV (psm) for within-ethnicity transactions and for cross-ethnicity transactions. We use repeated sale subsample to identify seller and buyer ethnicity group. Panel A reports the histogram of COV (psm) for within-ethnicity transactions. The average COV (psm) of 3570 within-ethnicity transactions is SGD336.15, which is reported with vertical red dot line. Panel B reports the histogram of COV (psm) for cross-ethnicity transactions. The average COV (psm) of 289 within-ethnicity transactions is SGD292.88, which is reported with vertical red dot line.

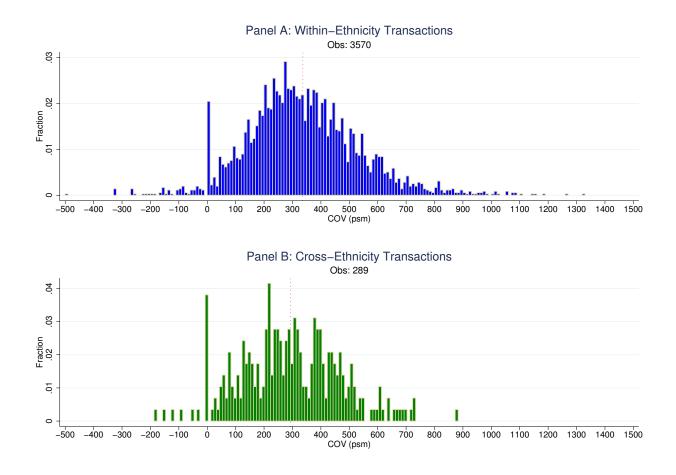
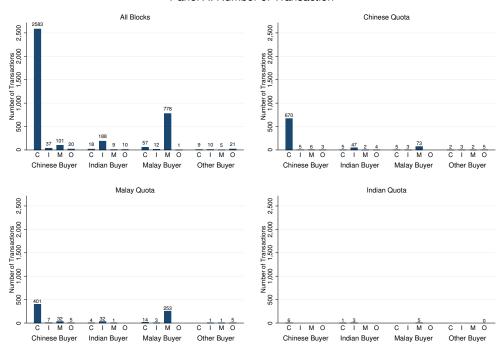
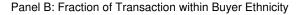


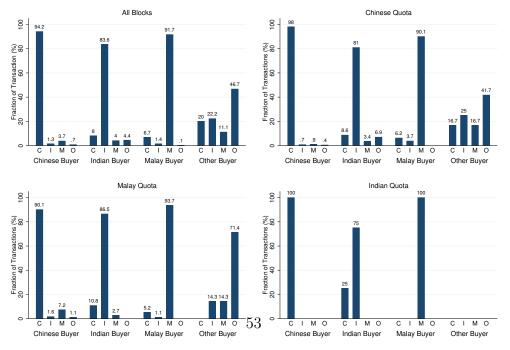
Figure 7: Matching between Ethnicity Groups

The figure reports the distribution of ethnicity matching between buyers and seller. We use repeated sale subsample to identify seller and buyer ethnicity group. Panel A reports the number of transactions by buyers' and sellers' ethnicity. First figure reports the matching between ethnicity groups in all blocks. For each ethnicity buyer, numbers of transactions with Chinese, Malay, Indian, and Others are reported. Second figure reports the matching in Chinese quota blocks, third figure reports the matching in Malay quota blocks, and fourth figure reports the matching in Indian quota blocks. Panel B reports the fraction of seller ethnicity for each ethnicity buyer from Panel A.



Panel A: Number of Transaction





Appendix Table 1: Distribution of Ethnicity Quotas in Singapore

We report the spatial distribution of ethnicity quotas in Singapore. HDB Town is a collection of neighborhoods/blocks and there are 26 HDB town in Singapore. Out of 8194 blocks in our sample, there are 2280 blocks with Chinese quota, 1368 blocks with Malay quota, and 82 blocks with Indian quota.

HDB Town	Chinese Quota	Malay Quota	Indian Quota	Total
A 3.6 TZ:	005		4	222
Ang Mo Kio	235	4	1	332
Bedok	36	146	1	462
Bishan	147	1	3	222
Bukit Batok	39	79	7	342
Bukit Merah	272	1	2	336
Bukit Panjang	30	15	5	288
Bukit Timah	22	0	0	26
Central Area	42	0	4	59
Choa Chu Kang	26	41	1	441
Clementi	54	13	0	167
Geylang	88	46	1	232
Hougang	274	2	4	518
Jurong East	37	36	2	214
Jurong West	61	129	4	640
Kallang/Whampoa	144	6	8	240
Marine Parade	10	3	0	52
Pasir Ris	12	154	1	400
Punggol	73	0	0	166
Queenstown	108	1	1	176
Sembawang	18	0	0	167
Sengkang	193	0	0	395
Serangoon	109	1	3	229
Tampines	15	278	0	684
Toa Payoh	181	1	4	267
Woodlands	2	356	14	607
Yishun	36	54	14	492
Total	2,280	1,368	82	8,194

Appendix Table 2: Distribution of Ethnicity Quotas in Singapore

We expand the results in Table 4 by year for Figure 5. We report the panel regressions of buyer's ethnicity and the presence of same ethnicity group in the block (discrete measure) on COV per square meter (COVpsm) by year. The dependent variable is COVpsm, winsorized at 1% level. Column (1) includes a dummy variable for Chinese buyer (I_Buyer Ethnicity) interacted with year dummies and interactions of them with dummies for ethnicity quota on the block. I_Chinese Quota equals 1 if the block has binding Chinese quota and equals 0 otherwise. I_Malay Quota equals 1 if the block has binding Chinese quota and equals 0 otherwise. I_Malay Quota equals 1 if the block has binding Chinese quota and equals 0 otherwise. I_Indian Quota equals 1 if the block has binding Chinese quota and equals 0 otherwise. I_Indian Quota equals 1 if the block has binding Chinese quota and equals 0 otherwise. Independent variables include Size (sqm) and Unit Floor. We also include year fixed effects, month fixed effects, block fixed effects, and property type fixed effects. Column (2) is about Malay buyer and column (3) is about Indian buyer with same setup as in column (1). The table reports point estimates with heteroskedasticity robust t-statistics in parentheses. ***, **, * denotes 1%, 5%, and 10% statistical significance.

	(1)	(2)	(3)
Variables	Chinese Buyer	Malay Buyer	Indian Buyer
I_Buyer Ethnicity \times I_2007	-89.24***	-172.2***	-126.4^{***}
	(-27.81)	(-33.34)	(-13.16)
I_Buyer Ethnicity \times I_2008	2.216	-75.83***	-37.61^{***}
	(0.795)	(-14.17)	(-4.335)
I_Buyer Ethnicity \times I_2009	-108.3***	-157.0***	-134.8***
	(-43.27)	(-40.97)	(-17.47)
I_Buyer Ethnicity \times I_2010	82.73***	7.536*	49.74***
	(32.53)	(1.781)	(6.714)
I_Buyer Ethnicity \times I_2011	117.0***	41.96***	76.08***
	(43.53)	(12.07)	(10.80)
I_Buyer Ethnicity \times I_2012	98.13***	21.53***	41.27***
	(38.69)	(6.812)	(6.452)
I_Buyer Ethnicity \times I_2007 \times I_Chinese Quota	86.27***	-49.10**	-56.23***
	(12.17)	(-2.427)	(-2.592)
I_Buyer Ethnicity \times I_2008 \times I_Chinese Quota	35.46***	-47.19***	-60.68***
	(5.813)	(-3.116)	(-2.655)
I_Buyer Ethnicity \times I_2009 \times I_Chinese Quota	-7.167	-65.14^{***}	-55.08^{***}
I Durren Ethnisitu y I 2010 y I Chinese Quete	(-1.283) 47.48^{***}	(-5.591) -36.64^{***}	(-3.585) -42.12^{**}
I_Buyer Ethnicity \times I_2010 \times I_Chinese Quota	2 · · · · · · · · · · · · · · · · · · ·		
I_Buyer Ethnicity \times I_2011 \times I_Chinese Quota	(8.637) 43.88^{***}	(-2.794) -55.34^{***}	(-2.470) -89.05^{***}
1_Duyer Ethnicity × 1_2011 × 1_Onnese Quota	(7.639)	(-5.856)	(-5.987)
I_Buyer Ethnicity \times I_2012 \times I_Chinese Quota	67.15***	-41.25***	-35.49***
	(12.01)	(-4.873)	(-2.674)
I_Buyer Ethnicity \times I_2007 \times I_Malay Quota	-29.23***	1.926	-21.62
	(-4.920)	(0.237)	(-1.026)
I_Buyer Ethnicity \times I_2008 \times I_Malay Quota	-4.704	-7.528	-5.690
	(-0.848)	(-0.928)	(-0.342)
I_Buyer Ethnicity \times I_2009 \times I_Malay Quota	16.04***	20.15***	28.57^{**}
	(3.287)	(3.278)	(1.970)
I_Buyer Ethnicity \times I_2010 \times I_Malay Quota	-26.50***	4.576	-24.08
	(-5.387)	(0.678)	(-1.557)
I_Buyer Ethnicity \times I_2011 \times I_Malay Quota	-5.469	18.77^{***}	22.23
	(-0.998)	(3.116)	(1.530)
I_Buyer Ethnicity \times I_2012 \times I_Malay Quota	-14.02***	11.20^{**}	11.23
	(-2.842)	(2.167)	(0.893)
I_Buyer Ethnicity \times I_2007 \times I_Indian Quota	-33.99	53.99	-46.46
	(-0.787)	(1.153)	(-0.811)
I_Buyer Ethnicity \times I_2008 \times I_Indian Quota	17.75	-60.65	12.48
	(0.430)	(-1.206)	(0.442)
I_Buyer Ethnicity \times I_2009 \times I_Indian Quota	-6.741	88.35***	136.7
I Derror Ethnicity VI 2010 v I Indian Oracte	(-0.224)	(2.938)	(1.558)
I_Buyer Ethnicity \times I_2010 \times I_Indian Quota	-30.16	88.57 (1.401)	-7.536
I Purron Ethnigity V I 2011 V I Indian Quata	(-1.091)	(1.401)	(-0.144)
I_Buyer Ethnicity \times I_2011 \times I_Indian Quota	14.26 (0.305)	-8.672 (-0.153)	67.83 (0.905)
I_Buyer Ethnicity \times I_2012 \times I_Indian Quota	-30.50	-8.498	(0.903) -4.561
1_Duyer Ethnicity ~ 1_2012 ~ 1_indian Quota	(-0.691)	(-0.151)	(-0.125)
	(-0.091)	(-0.101)	(-0.120)