

Why Do Real Estate Agents Buy Houses at Lower Prices? Cherry Picking or Bargaining Power

Sumit Agarwal¹, Jia He², Tien Foo Sing³, Changcheng Song^{4*}

Date: Dec 2015

Abstract

Real estate agents play an important intermediary role in housing markets. We use a merged transaction dataset that identifies houses purchased by registered real estate agents (salespersons) and other buyers in Singapore to empirically test the hypothesis that real estate agents use information advantages to buy houses at bargained prices. We estimate that agents bought their own houses at prices that are 2% lower than comparable houses bought by other buyers. Discounts for houses bought by agents for their own use have diminished after the new regulatory regime has been introduced in 2010. We compare agents' transactions that involve two different groups of sellers. The first group includes weak sellers, who are individuals facing time pressure to sell their current houses before moving into new houses, and distressed sellers affected by lawsuits, and the second group includes strong sellers, such as investors who sell houses for positive investment returns. We find no evidence that agents use information advantages to "cherry pick" weak sellers in housing transactions. However, our results support the bargaining power hypothesis that agents use information advantages to obtain lower prices when buying their own houses from individuals and distressed sellers.

JEL Classification: D14, R30, E51

Keywords: *Housing Market, Real Estate Agents, Information Advantages, Cherry Picking, Bargaining Power, Agency Problem, Market Distortion*

* National University of Singapore. We are benefited from the comments of Souphala Chomsisengphet, David Laibson, Jessica Pan, Ivan Png, Nagpurnanand Prabhala, Wenlan Qian, Tarun Ramadorai, David Reeb, Amit Seru, Nick Souleles, Bernard Yeung, and seminar participants at the National University of Singapore. All errors are our own. We are also extremely grateful to William Lai and Christopher Ng Gon Chew for the data supports.

1 Departments of [Finance](#) and [Real Estate](#), National University of Singapore, BIZ1-07-69, Mochtar Raidy Building, 15 Kent Ridge Drive, Singapore, 119245, Singapore (email: ushakri@yahoo.com)

2 Department of Finance, School of Finance, Nankai University, #94 Weijin Road, 300071 Tianjin, P.R. China (email: hejia@nankai.edu.com)

3 Department of Real Estate, National University of Singapore, SDE1-05-17,4 Architecture Drive, Singapore 117566, Singapore(email: rststf@nus.edu.sg)

4 Department of Economics, National University of Singapore, 1 Arts Link, AS2 05-37, Singapore, 117570, Singapore (email: ecsscc@nus.edu.sg)

1. Introduction

Real estate agents play an important intermediary role in housing markets. They use their local market knowledge to bridge the information gap between potential buyers and sellers. They reduce search costs and improve matching between buyers and sellers. Buyers and sellers pay a commission to real estate agents, usually a fraction of the transaction price¹, after they have brokered a real estate deal. Agency problems arise when interests between house buyers/sellers and real estate agents are misaligned. If real estate agents are merely motivated by commissions, they will try to close deals in the shortest possible time, rather than to get the “best” attainable prices for their clients. The incremental effort needed to obtain the best price for clients is not commensurate with marginal increases in commissions they will receive.

Previous studies apply two different strategies to test the agency problem. The first strategy compares housing transactions with and without agents. Hendel, Nevo and Ortalo-Magne (2009) find no evidence that houses sold via the Multiple Listing Service (MLS) networks command premiums relative to those sold by owners using the For-Sale-By-Owner (FSBO) platform. Based on the listing data obtained from Stanford University’s Faculty Staff Housing (FSH) office, Bernheim and Meer (2013) find that using full-service brokers reduces sale prices of a typical home by 5.9 to 7.7 percent. The results imply that local knowledge and expertise provided by real estate agents in the MLS listings are not correlated with higher house selling prices. They argue that broker services should be unbundled from MLS listings. The second strategy compares agent’s own housing transactions and clients’ housing transactions. Rutherford, Springer and Yavas (2005) show that agents sell their own houses for a premium of approximately 4.5%, whereas Levitt and Syverson (2008b) find that houses owned by real estate agents sell for about 3.7 percent more than other houses. The evidence suggests the presence of agency problems in the housing market. In a recent study by Allen, Rutherford, Rutherford and Yavas (2016), they use Miami-Dade County MLS data and find that agent-buyers pay 4% lower than comparable houses purchased by individual buyers. There is no significant information advantages when agents buy houses from other agent-sellers.

Earlier studies invariably focus on the sale-side activities of real estate agents in the US. Our paper also uses buy-side activities of real estate agents from a unique set of Singapore’s data. Following the second strategy, we empirically test if agents use information advantages to buy own houses at prices lower than houses they broker for other buyers. We merge a dataset consisting of more than 100,000 private housing transactions with a dataset of real estate agents (salespersons) registered with the Council of Estate Agencies (CEA). The merged dataset allows us to identify houses purchased by agents for their own use (the “treatment” group) and houses

¹ In the US, the commission rates range between 5% and 6%. Prior to September 2008, real estate agents in Singapore charge about 1% commission on sellers for a transaction in the private housing market. Buyers usually do not have to pay commission to an agent.

bought by other buyers (the “control” group). We test if prices of agent-own houses are lower than comparable houses purchased by non-agent buyers.

We design two strategies in our analysis. First, we use the establishment of a new regulatory watchdog in Singapore – the CEA, on 22 October 2010 as an exogenous policy shock. Second, based on sellers’ identities in the transaction data, we sort the sellers into three distinct groups - individuals, investors and institutions. For individual sellers, we merge the sellers’ data to a dataset on law events, such as car accidents, credit cards default, bankruptcy and others. Like in Garmaise and Moskowitz (2004), we test if price differences (discounts/premiums) are observed when agents buy houses from different sellers (uninformed individuals, and informed investors/institutions).

Our results show that real estate agents bought their own houses at about 2% lower prices than houses bought by individuals. We test the effects “before” and “after” the establishment of the CEA in a *difference-in-differences* (diff-in-diff) setup, and find that discounts for houses purchased by agents for own use decreased after the introduction of CEA in 2010.

Why do real estate agents pay lower prices when buying their own houses? There are two possible channels via which agents could exploit information advantages. First, agents use information advantages to “*cherry pick*” bargained deals from weak sellers. For example, agents buy houses from distressed sellers, who were involved in lawsuits. Second, agents use information advantages to tilt their bargaining power against weak sellers, who face time pressure to sell their houses quickly.

Since the main sellers in the new sale market are developers, we restrict our sample to resale market to analyze the channels. We use two groups of sellers - individuals and distressed sellers who are involved in lawsuits, to represent weak sellers. Individual sellers are identified as owner-occupiers if he/she lives in a house with the same address as that of a transacted house. We compare the weak sellers with the control group that include two types of strong sellers - investors and institutions. Investors are identified if his/her current home address is different from the address of a transacted house. In the resale market, institutions (firms) sell houses that are no longer required for their foreign executives. Compared to investor sellers, individuals are more likely to be under tighter time pressure to quickly sell their current houses before moving into their new houses. We find no evidence that agents exploit information advantages to cherry pick weak sellers in housing transactions. However, we find strong evidence that agents pay lower prices when buying houses for their own occupation from “individuals” and “institutions”, but no price discounts are found for houses bought from investors. The results are consistent with the bargaining power story implying that agents use information advantages to obtain price discounts when buying houses from “weak” sellers.

We use sellers involved in lawsuits, such as bankruptcy, car accidents, sales of goods, credit cards, and tenancy disputes, as the second proxy for weak sellers, but find no evidence that agent-buyers are more likely to buy houses from these distressed sellers. However, we find evidence that agent-buyers pay lower prices relative to non-agent buyers when buying houses for own use from these distressed sellers. The results again support the bargaining power story.

One possible explanation for the agents' discounts is flipping, where agents buy houses and resell them quickly for profit. The flipping story should lead to two outcomes. First, we should observe a large volume of houses sold by agents in the market; and second, agents should enjoy larger discounts when they buy houses for investment purposes. Our results, however, are unlikely to be explained by the flipping story. Agents' transactions constitute only 8.1% of the housing sales in our sample. Agents pay 2.1% lower in prices than non-agents when buying houses for own use. We do not observe larger discounts for houses bought for investment purposes by agents. The second possible explanation for the agents' discounts is that agents time the market to obtain larger price discounts when buying house for their own use. The timing story implies that agents' transactions are more likely to bunch around a selected time in a year. However, we find that transactions by agent-buyers are uniformly distributed constituting between 5 percent and 5.6 percent of the total sales across the 12 months. No significant variations in discounts in agents' transactions are observed, when the transactions are sorted by months, lending costs and housing price index. Therefore, it is unlikely that agents choose to time the market when buying houses.

Our paper makes three contributions to the literature. First, we find new empirical evidence to support the findings of Rutherford, Springer and Yavas (2005), and Levitt and Syverson (2008b) that real estate agents exploit information advantages to buy their own houses at prices that are lower than comparable houses bought by the individual. The earlier findings use data from the sell-side activities; whereas we find new evidence of real estate agents exploiting information advantages from the buy-side activities of housing markets. We verify the hypothesis that experts use information advantages to cause distortion to housing markets.

Second, we identify the channels via which information advantages are used by real estate agents in finding bargained deals. Unlike Garmaise and Moskowitz (2004), we do not find evidence to show that agent-buyers self-select to trade with uninformed sellers (individuals). We show that agent-buyers pay lower prices when buying houses for their own use from individual (weak) sellers. However, agent-buyers could not use the bargaining power to obtain lower prices for houses bought for own use from informed sellers (investors). We also show that the bargaining power story is not correlated with adverse selection by agent-buyers. They do not have prior knowledge of sellers' involvements in law events, but they use information advantages to obtain discounts in housing transactions after sellers' credit conditions have been revealed in the post-law events.

Third, our paper is also related to the literature on competition and market distortion. Standard economic models predict that competition eliminates market distortion. In the presence of shrouding attributes and consumer myopia, competition dissuades firms to reveal information that improves market efficiency (Gabaix and Laibson 2006). In the open-ended fund industry, competitive fund managers increase fund supply without improving market efficiency (Stein 2005). We use the establishment of CEA as a regulator of real estate brokerage industry in 2010 to set up a natural experiment. Prior to the CEA regime, a dual representation model is not prohibited, where a real estate agent could concurrently represent a buyer and a seller in the same housing transaction. In this unregulated market, inefficiency arises if an agent shrouds information from unsophisticated (myopic) buyers and sellers. The presence of CEA has effectively weeded out unethical practices that cause market distortion, which include the dual representation by agents. We show that discounts in agent-buyer transactions have diminished in the post-CEA after 2010. The results imply that unethical practices that cause market distortion, such as collusion (Levitt and Syverson, 2008a) and information shrouding (Gabaix and Laibson 2006), could be mitigated in a competitive real estate brokerage market.²

The remainder of the paper is organized as follows. Section 2 gives a brief overview of real estate brokerage industry in Singapore. Section 3 discusses empirical data and descriptive statistics. Section 4 sets up the empirical strategy and analyses empirical results. Section 5 concludes the study.

2. Real Estate Brokerage Industry in Singapore

Singapore is an island nation with a land area of about 716 square kilometers. As of 2013, it has a population size of 5.47 million, which includes 3.34 million citizens and 0.527 million permanent residents. The population is composed of a diverse mix of ethnic groups including 74% Chinese, 13% Malays, 9% Indians, and 3% of other races.³ Singapore's home ownership rate of more than 90% is one of the highest in the world. 81.55% of the total housing stocks, estimated at 1.152 million units, are made up of public housing built and sold by the government (as of 2012). We use non-landed private housing transactions in our empirical analyses. Non-landed housing, which includes condominiums and apartments⁴, is the largest segment of the private housing market constituting 12.14% of the total private housing stocks.

² Hsieh and Moretti (2002) and Barwick and Pathak (2011) argue that low entry barriers in the real estate brokerage industry could influence commission rates and also efficiency of real estate brokers.

³ These and the following statistics of Singapore's population and housing market are drawn from the *Population trends 2014*, Department of Statistics, Singapore.

⁴ Condominiums and apartments are both high-rise and high density residential development. Condominiums are projects with full-facilities and built on lands with a minimum size of 0.4 hectare. Whereas, apartments are projects with limited facilities built on smaller parcels of land. There are no restrictions on foreign ownership in condominium projects, but foreigners could only purchase apartments that are 6-storeys or higher under the Residential Properties Act.

In Singapore, the CEA is as a statutory board established under the realm of the Ministry of National Development (MND) on 22 October 2010.⁵ The missions of the CEA are twofold: (i) to raise the professionalism of the real estate agency industry; and (ii) to protect the interests of the consumers. It is empowered by the Estate Agents Act (Chapter 95A) to regulate practices of licensed agents and salespersons in real estate markets. As of 31 March 2013, there were 1,495 real estate agency firms and 32,982 real estate salespersons (agents) registered with the CEA.⁶

In Singapore, real estate agents charge a commission on a seller at about 1% to 2% of the sale price when they close a transaction in the private housing markets. Buyers do not usually pay a commission to a seller agent in any transaction. It is also not mandatory for buyers to appoint a buyer agent in a transaction. However, in some cases, where specific requirements on the type and/or location of property are instructed by a buyer in brokerage contracts, a pre-agreed commission will be charged by a buyer agent, if he/she has fulfilled the requirements. After 2010, the CEA disallows dual representation arrangement, such that an agent is not allowed to concurrently represent both a seller and a buyer in any transaction.

3. Data Sources and Analyses

3.1. Data Sources

We collect data from four different sources in our empirical analyses. The first dataset comprising private (non-landed) housing transactions recorded in the caveats for the period from January 1995 to December 2012 was obtained from a proprietary source. The data contain information on property attributes, such as property type (condominium or apartment), tenure, unit size, floor level and address, and transaction details, such as sale type (new sale, sub-sale, or resale)⁷, transaction date, transaction price, and buyers' and sellers' profiles, such as names and their unique personal identification numbers.

Unlike in the US, the multiple listing service (MLS) system is not widely used in Singapore.

⁵ Prior to the establishment of the CEA, real estate agents are informally regulated by two professional bodies, which are Institute of Estate Agents (IEA) and Singapore Accredited Estate Agencies (SAEA) Limited. These two professional bodies did not have statutory power to license agents and/or bar unethical agents from practicing in Singapore.

⁶ Under the Estate Agency Act, the two terms, "estate agent" and "salespersons", have legal interpretation and meanings. The CEA defines "estate agents" as estate agency businesses (sole proprietors, partnerships, and companies), and "Salespersons" as individuals who perform estate agency work. However, we use "real estate agents" and "salespersons" interchangeably to represent, individuals, who are licensed to conduct real estate brokerage services for buyers/sellers of houses.

⁷ There are three sale categories recorded in the transaction data. "New sale" and "sub-sale" consist of pre-completion units sold in the primary markets. The former includes units marketed and sold by developers in new launches, whereas, the latter includes units bought and sold by individual buyers before the project completion. "Resale" refers to the sales of completed units in the secondary markets.

Real estate agents in Singapore use print media, such as newspapers, magazines and flyers, and also electronic portals to advertise and disseminate information on houses for sales. It is difficult to identify the time when a house is first put up for sale in the market. Therefore, we are not able to test the effects of time-on-market for housing transactions in Singapore as in Levitt and Syverson's (2008b) study, where the listing data are captured in the MLS records.

The second proprietary dataset contains demographic information of about 70% of Singapore's residents. Based on the unique identification numbers, we match sellers in the transaction dataset to the population dataset to obtain information on their current home addresses. By comparing transacted property addresses and residence addresses of the sellers, we sort them into one of the categories, either as individuals (owner-occupiers) or investors. If a seller is a firm, it will be included into the third category known as "institutions". While these three categories of sellers were involved in resale transactions, we also separately identify new houses sold by developers in the primary (pre-completion) market.

The third dataset covers a full list of licensed real estate salespersons (agents) published in the public register of the CEA website as in May 2014. The data include information on salesperson's name, name of affiliated estate agency/firm, and register number of the salesperson. We match the names of salespersons to the names of buyers in the transaction dataset to identify agent-buyers (the treatment group) and non-agent buyers (the control group).⁸

The last dataset consists of records of law events in Singapore's Courts for the same period from 1995 to 2012. The law event records contain information on registration time, nature of claim, level of courts, and outcomes. Based on the unique personal identification numbers of plaintiff(s) and defendant(s) in each law event, we merge the law event dataset to the property transaction dataset.

3.2. *Descriptive Statistics*

After merging the data on buyers, sellers, and law events into a master transaction data file and sieving out transactions with incomplete or wrong information, our final sample contains a total of 108,534 transactions. Out of the total sample transactions, 5775 (5.32%) are agent-buyer transactions (treatment group) and 102,759 (94.68%) are non-agent-buyer transactions (control group). Figure 1 shows the frequency of transactions by year for: (A) the full sample, and (B) the agent-buyer sample, for the period from 1995 to 2012. The trends of the two sets of transactions are quite similar, and the highest sale numbers were recorded in 2009.

*** Insert Figure 1 about here ***

⁸ There are a small number of cases with similar names, in both buyers' or agents' files, and robustness tests are done on these "duplicated" matched samples to remove possible biases.

Figure 2 plots the kernel density of house price per square meter (\$psm) for the agent-buyers and the non-agent-buyers. The line representing unit housing prices for the non-agent buyers is shifted slightly to the right indicating that houses bought by the non-agent-buyers are more expensive than houses bought by agent-buyers.

*** Insert Figure 2 about here ***

We estimate the average unit prices by year for houses bought by the agent-buyers and the non-agent-buyers, and also the differences between the two averages. Figure 3, Panel A shows that the average house prices for the agent-buyers are lower than the average house prices for the non-agent-buyers. Except in 1999 and 2008, the average prices of the agent-buyers' houses are lower in all years than the average prices of the non-agent buyers' houses (unadjusted for housing quality). The largest discounts of more than 5% (negative price differences) are estimated in 1997. Panel B shows the proportion of agent buyers by years.

*** Insert Figure 3 about here ***

We estimate the average unit house price by month for the agent-buyers and the non-agent buyers, and test whether there are "month" effects on agent discounts. Figure 4, Panel A shows that the average house prices for the agent-buyers are lower than the average prices of houses bought by the non-agent-buyers. The agent-buyers pay lower prices than the non-agent buyers for houses bought in all the months (unadjusted for housing quality). Panel B shows that the agent buyers' sales constitute about 5 percent to 5.6 percent of the total sales across the 12-month period.

*** Insert Figure 4 about here ***

Panel A and Panel B of Figure 5 show the kernel density plots of unit house prices for the agent-buyers and the non-agent buyers in the resale market and the new sale market, respectively. The figures show that the unit housing price distributions in both the resale and the new sale markets are skewed to the right, which indicate that houses with unit prices below \$10,000 per square meters (psm) make up a large fraction of the transactions in the two markets. Houses in this price range appeal to a large proportion of buyers in the mass private housing market; whereas, houses in the luxury segment are usually priced above S\$20,000 psm, and they are bought by wealthy individuals and investors. The high-end condominiums are usually bought by buyers for long-term investment purposes. This market is less liquid, and fewer transactions are observed in this segment of the market.

*** Insert Figure 5 about here ***

In the resale market (Panel A), we observe that agent-buyers dominate the transactions in two

segments of the housing markets, which are the segment with the average prices below S\$6,000 psm, and the segment with prices ranging between S\$10,000 psm and S\$12,000 psm. The non-agent buyers are active in the transactions in the two extreme tails, which include houses that are below S\$5,000 (left-tail), and those with prices above S\$14,000 psm (right-tail).

In the new sale market consisting of pre-completed houses sold by developers (Panel B), we observe similar patterns in the housing price distributions based on the Kernel density plots for the agent-buyers and the non-agent buyers. The agent-buyers are active in three segments of the new sale market, which include houses in the three price ranges: between S\$5,000 psm and S\$6,000 psm, between S\$9,000 psm and \$10,000 psm, and between \$12,000 psm and S\$13,000 psm. The agent-buyers' transactions are relatively thin in the low-end segment of the market with housing prices below S\$4,000 psm. The kernel density plots show the dynamics of housing transactions in the two markets.

We compute the differences in average unit prices (S\$psm) for houses bought by the agents and the non-agents as a percentage of the average unit house prices (S\$psm) at the district levels, and plot them in Figure 6. The figure shows the variations in price for houses bought by the agents and the non-agents by district. The price differences are bounded within a range between -6% and 6%. The vertical bars that are below (above) the zero line indicate the price discounts (premiums) for houses bought by the agents for own use relative to comparable houses bought by other buyers. Agents pay the highest price premiums for houses bought in District 1, which include areas near the downtown, such as Raffles Place, Marina, and Cecil; and District 14, which cover areas in Geylang, Paya Lebar, and Sims. However, agents bought houses with the largest discounts relative to other non-agents buyers in District 2 (Tanjong Pagar and Chinatown), District 7 (Bugis, Beach Road, and Golden Mile) and District 21 (Upper Bukit Timah, Ulu Pandan, and Clementi Park).

*** Insert Figure 6 about here ***

Table 1 reports the descriptive statistics of the main variables sorted by the full sample, the agent-buyers (treatment sample), and the non-agent-buyers (control sample), respectively. Panel A reports the statistics for the original sample, and Panel B reports the statistics for the paired samples derived using the propensity score matching approach. Panel A shows that the average per square meter (psm) transaction price for the full sample of 108,534 houses is estimated at S\$8,245.58 psm. The average unit price of S\$8,127 psm is estimated for the agent-buyer sample (5,775 houses), which is 1.5% lower than the average unit price of S\$8,252 psm for the non-agent-buyer sample (102,759).

*** Insert Table 1 about here ***

We use the propensity score matching (PSM) technique to create a control group of buyers with matched characteristics, which include hedonic attributes, transaction year, property location and buyer characteristics. Based on the propensity scores of the agent-buyers' transactions (the treatment group), we construct a balance sample of the non-agent buyers (the control group) using one-to-one matching process. As shown by the descriptive statistics of the 5,701 matched samples in Panel B of Table 1, except for the transaction prices, the characteristics of the original buyer-agent sample, in term of housing attributes, and demographic characteristics of buyers, match the characteristics of the non-agent control sample generated by the PSM method. The average unit price of the agent-buyer group is estimated at S\$8,123 psm, which was 1.63% lower than the average unit prices of S\$8,258 psm estimated for the non-agent-buyer group.

4. Empirical Strategy and Results

4.1. Do agents buy houses at lower prices?

We test whether there are price differences in houses bought by the agent-buyer group (treatment) and the non-agent-buyer group (control) controlling for the spatial and the time fixed effects. The model specification is given below:

$$\ln(P_{i,d,t}) = \alpha + \beta \times \text{Agent}_{it} + \gamma \mathbf{X}_i + \mu_d + \varphi_t + \varepsilon_{itd} \quad (1)$$

where the dependent variable $\ln(P_{i,d,t})$ is the log unit sale price (S\$psm) for house i located in a planning region d at time t . Agent_{it} is a binary indicator that has a value of 1, if a buyer is an agent; and 0 otherwise for the non-agent-buyer. \mathbf{X}_i is a vector of regressors on hedonic attributes of housing, such as housing type, floor level, sale type, and buyer's characteristics, such as race (Chinese, Malay, Indian/Others), gender and marital status. μ_d and φ_t are the spatial fixed effect and time fixed effects. α , β and γ are the estimated regression coefficients, and ε is the residual term of the regression.

*** Insert Table 2 about here ***

Table 2 presents the main results. We estimate the *log-price* models as in Equation (1) using (a) the full sample (Columns 1 and 2); (b) the sub-sample of repeated sales (Columns 3 and 4); and the matched sample (Columns 5 and 6). The main results (Columns (1) and (2) of Table 2) show that agents buy their own houses at prices that are 1.99% lower than comparable houses brought by other buyers. The results remain significant after controlling for the district and the year fixed effects; and agents pay 1.88% lower for their own houses than comparable houses bought by others.⁹

⁹ We test the heterogeneous effects of agent buyer on housing price. We find that the price discount is lower when the buyers are older or married.

One potential concern is that our dataset includes only agents listed on the CEA website as in May 2014. Some non-agent buyers may be potentially misclassified as agent buyers, if they become agents after they bought their houses. Similarly, some agent-buyers may also be misclassified as non-agent buyers, if they quit their agent jobs after they bought their houses. The misclassifications, if exist, are expected to bias our results toward zero. Thus, the agent discounts are likely to be at the lower bound of our estimation.

We conduct further robustness checks on the results. First, we test whether our results are driven by agent's selection on unobserved quality of houses. We use the sub-sample (b) that includes only 2,874 houses sold for more than once, of which one of the sales involves agent-buyers. We add the house fixed effects to control for unobserved quality of houses. Based on the same rationale of the repeated sale methodology, we compare differences in sale prices while keeping the quality of houses constant by using sample houses that sell twice or more, and one of the buyers was an agent. Despite a smaller sample of repeated sales used in the estimation, the results show that the coefficient on the agent dummy is significant at -1.57% (Columns 3); and the coefficient is -1.48% (Column 4), when the socio-economic characteristics of buyers are controlled for. The results imply that for repeated transactions – one by an agent-buyer and another one by a non-agent buyer, we expect agents to pay a lower price when buying the house for their own use compared to buying the same house for clients (other buyers).

In the second robustness test, we test if our results are influenced by unbalanced samples in the treatment group and the control group. Based on the buyers' loading factors estimated by the PSM technique, we match the housing samples in the treatment group one-on-one onto the control group. We rerun the log-housing price models using the matched samples. The results in Columns (5) and (6) of Table 2 show that agents pay 1.7% lower for houses bought for their own use compared to similar houses bought by other non-agents. The price difference between agents' houses and non-agents' houses is still significant at -1.69% after controlling for the buyers' characteristics.

The findings in Table 2 using different samples are generally robust and consistent. The results support the hypothesis that agents do use their information advantages to buy their own houses at prices that are lower than comparable houses bought by other non-agents.

We also test the robustness in the process of merging the agent dataset and the transaction dataset. We identify the agent-buyers by matching more than 30,000 registered agents (salespersons) to the housing transactions. We are able to match a large number of agents, who have bought houses during the sample periods. After cleaning transactions with missing key variables, 8,626 buyers are identified as the agent-buyers. In the matching process, cases with more than one match, based on the buyer names in the transaction dataset and the agent names in the agent list,

are separated and denoted as “agents with multiple matching names”. The main results (Table 2), are estimated using only agents with “one-to-one matching names”; and agents with multiple matched names are dropped from the sample. The process may cause possible exclusion biases to the results. As robustness checks, we test if our results will be distorted by the random elimination of agents with multiple matched names in our samples. We adopt two strategies in our tests: First, we use all agents with multiple matching names in the sample (Left-hand Panel of Table 3); and second, we randomly select one agent from agents with multiple matching names (Right-hand Panel of Table 3). We repeat the estimation using the full housing samples, and also use the propensity score matching (PSM) technique to construct a balanced sample of the agent-buyers and the non-agent buyers. The results are summarized in Table 3.

*** Insert Table 3 about here ***

The results show that when all agents with multiple matched names are included, our results are still significant and consistent, but the estimates are biased downward, which could be caused by “false” inclusion of non-agents into the agent group. The coefficients on agents’ price discounts are estimated at 1.32% in the full sample, and 0.93% in the balanced sample, respectively, compared to 1.88% and 1.66% found in the main results (Table 2). When we use only one randomly chosen agent from the sample of agents with multiple matched names, the results remain strong and consistent. We estimate the price discounts of 1.63% and 1.33% in the full sample and the balanced sample, respectively, which are closer to the main results in Table 2. These results are consistent with the information advantages story that agents pay lower prices for their own houses than comparable houses bought by non-agent buyers.¹⁰

We then test the heterogeneous effects by the housing sale type: new sale and resale. In Singapore and many Asian markets, it is common for developers to start selling their housing units before physical completion of a project; and the practice is known as “pre-completion sales”. It is also common for developers to outsource marketing and brokerage services of new residential projects to third-party real estate agencies. Real estate agencies are appointed because of their teams of trained real estate salespersons/agents and established sale networks. Real estate agents working for real estate agencies will obtain information advantages because of their first-hand knowledge of listing prices for all units available for sales in the projects. In weak markets, agents are usually the first to know when discounts and other forms of incentives are dangled by developers to attract buyers. Therefore, real estate agents do have information advantages relative to other buyers in the new sales residential market. Unlike Hendel, Nevo and Ortalo-Magne (2009) and other US studies that have excluded developers’ new sales from their samples, we split our housing transactions into two groups: new sales versus resale sales¹¹, and

¹⁰ In the sample of agents with “one-to-one matching names”, it is still possible that buyers with the exact same names are different persons. Thus, some non-agent buyers are classified as agent buyers. In this case, our estimation of agent discounts are likely to be a lower bound.

¹¹ Resale market transactions include sales of completed properties, where prices are negotiated at arm-length basis

test the significance of agents' information advantages in the two distinct markets.

*** Insert Table 4 about here ***

We run separate agents' information advantage models (Equation 1) using the resale sample and the new sale sample separately. The results in Table 4 show that the discounts for houses sold to the agent-buyers are significant in both the resale and the new sale markets. In the resale market, the agent-buyers pay 2.20% (Column 1) lower than prices for comparable houses paid by other buyers, and the price discount is 2.15% (Column 2) after buyers' characteristics are controlled for in the model. The results show that the price discounts are higher than the discounts of 1.99% (Table 2, Column 1) and 1.88% (Table 2, Column 2) estimated in the full sample models. However, in the new sale market, the discounts for the agent-buyers are still significant, but the magnitude is smaller at 1.60% (Column 3), and 1.44% (Column 4) after controlling for the buyers' socioeconomic characteristics. The results again do not rule out the information advantages of agents when buying houses for their own use relative to other buyers in both the new sales and the resale markets. However, we expect the agent-buyers to obtain larger price discounts in the resale transactions relative to the new sale transactions.

We expect large agency firms with a larger pool of real estate agents to have higher probability of their agents exploiting information advantages to pay lower prices for houses bought for their own use. Agents hired in large agency firms are also likely to be more heterogeneous relative to agents in other agency firms. We use two "firm size" dummies to control for possible large firm effects in the empirical tests. The first "firm size" dummy has a value of 1, if an agency firm has 100 or less real estate agents (salespersons); and 0 otherwise (Table 5, Columns 1 and 2). The second "firm size" dummy identifies the medium and smaller agency firms, which has a value of 1, if a firm is not one of the 5 largest real estate agency firms by the number of real estate agents hired; and 0 otherwise for the top 5 firms by size (Table 5, Column 1 and 2). We rerun the OLS regressions with log-unit housing prices as the dependent variable, and include the "Agent×firm size" interactive term in the model. The empirical results are reported in Table 5.

*** Insert Table 5 about here ***

The results show that the agents' discounts are significant at about 1.81%, and at 1.91% when the two firms size dummies (firms with less than 100 agents and firms that are not in the top 5 rank by the agent size), and the models controls for socioeconomic characteristics of the buyers, district and year fixed effects. The interactive variables, "Agent x Firm Size" variables, however, are not significant in all models implying that there are no firm size impact on the agents'

by willing buyers and willing sellers, who are represented by their respective agents. The agents will be paid 1% commission when closing a transaction deal. We also run a robustness check where we combine the resale and sub-sale sample. The results are unchanged.

information advantages in buying own houses compared to other non-agent buyers.

4.2. *Effects of regulatory regime shift*

We use the establishment of the CEA in October 2010 as a natural policy experiment. We predict that the establishment of CEA should eliminate agent discount since it reduced the likelihood that buyers represented by agents were ripped off by conflict of interest in dual agency. If this is true, we should observe that adjust housing price for non-agent buyers declined after the policy change while adjust housing price for agent buyer did not. Figure 7 shows the adjusted housing price for agent and non-agent buyers over time. We find that adjust housing price for non-agent buyers decreased from 90.9 in 2010 to 88.3 in 2011. In contrast, adjust housing price for agent buyers decreased from 84.5 in 2010 to 87.7 in 2011.

*** Insert Figure 7 about here ***

We use the *diff-in-diff* specification below to analyze the impact of CEA establishment.

$$\ln(P_{i,d,t}) = \alpha + \beta \times \text{Agent}_{it} + \phi \times (\text{AfterCEA} \times \text{Agent}) + \gamma \mathbf{X}_i + \mu_d + \varphi_t + \varepsilon_{itd} \quad (2)$$

We include an interaction term, “Agent x AfterCEA”, where “AfterCEA” is a time dummy that indicates the post-CEA regime, in the *difference-in-differences* (diff-in-diff) framework. If the interactive term is positive and significant, we argue that the new CEA regulatory regime has effectively curtailed the effects of agents’ exploiting of information advantages to pay lower prices in housing purchases.

The results in Table 6 show that agents’ information advantages are economically and statistically significant as reflected by lower prices in their own housing purchase compared to houses bought by other non-agent-buyers, which are estimated at about 2.09% (Column 1) and 1.97% (Column 2).

*** Insert Table 6 about here ***

The coefficients on the interactive term “Agent×AfterCEA” are positive at 1.49% and 1.43%, respectively, but they are statistically insignificant in both models. The results indicate that the new regulatory regime via the CEA has strong “treatment” effects, which were shown by decreases in price (information) advantages of agents in the post-CEA period. The results imply that unethical practices, such as dual representation and information shrouding have been largely curtailed after the CEA regulatory regime has been introduced. The agents are no longer able to exploit their information advantages to buy own houses at prices lower than prices of comparable

houses paid by non-agent buyers.

We test the treatment effects using transactions occurring in the period between 2005 and 2012, which is closer to the CEA establishment period in October 2010. The results in Column 3 are robust and consistent with the earlier results in the full sample. In Columns 4 and 5, we test the impact of CEA using the new sale and resale data. The results are also robust and consistent with the earlier results in the full sample.

*** Insert Table 7 about here ***

We next run the placebo tests by using different cut-off dates to mimic the “treatment” effects of the establishment of the CEA. We systematically use different “arbitrary” treatment years to represent the placebo policy changes from 2004 to 2009. For each of the placebo policy year test, we keep a balance sample size by fixing the sample periods to 3 years before and 3 years after the placebo policy year. We run the tests using the 6-year rolling window, for example, in the 2004 placebo year, the samples used in the estimation span from 2001 to 2006. Table 7 presents only the results on the treatment effects (“Agent×Placebo cutoff year”), whereas, the coefficients for other variables are omitted due to space constraint. We find that except for the year 2005 (Column 2), the coefficients on the interaction terms are negative, though they are insignificant in the four Placebo years from 2004 to 2007. However, when the Placebo cutoff years are moved to 2008 and 2009, which are closer to “treatment” Placebo year in 2010, the coefficients on the “Agent×Placebo cutoff year” become positive, but are still statistically insignificant. The switch in the coefficient signs from negative in the Placebo years from 2004 to 2007 to positive in 2008 and 2009 Placebo years suggests that the treatment effects could not be falsified in the “Placebo” controlled tests.

Agents are no longer able to buy houses for their own use at prices lower than those bought by other clients following the implementation of regulatory controls in the post-CEA regime. One possible cofounder that we could not rule out is related to the use of online search portals and web-based listing services that have gained popularity after the subprime crisis in 2007. The technology advances in providing real estate listings could reduce the search costs, and also diminish information advantages of real estate agents in the housing markets. However, the timing is not consistent with our results in placebo test. In Table 7 Column 4, we show that the coefficients of “Agent×Placebo cutoff year” is negative. In column 5, it is positive and larger than 1 percentage points. It suggests that the shock happened around 2010 rather than 2007. Thus, the technology change is unlikely to explain our results.

4.3. *Channels of Agent Discounts*

Why do real estate agents pay lower prices when buying their own houses as shown by the empirical evidence in the earlier section? What are possible mechanisms through which real estate agents could exploit information advantages to gain economic benefits in housing transactions? There are two possible channels of information advantages. First, real estate agents use information advantages to “*cherry pick*” bargains in the markets. The selection channel is supported, if real estate agents show strong preference to buy houses from a particular group of buyers, such as uninformed individuals and/or buyers, who are financial distressed. Second, real estate agents use information advantages to tilt their bargaining power when negotiating against “weak” individuals, who are less informed. If the bargaining power channel is not rejected, we expect real estate agents to pay lower prices when buying houses from individual sellers relative to buying houses from more informed investors (sellers). They exploit their information advantages to bargain prices down when dealing against buyers, who are forced into “fire sales”.

4.3.1. *Agents’ Selection on Weak Sellers*

In testing the channel that real estate agents use information advantages to “*cherry pick*” weak sellers in the market, we use two types of sellers: individual sellers and sellers involved in lawsuits, to proxy weak sellers. We test the housing price effects of this group of weak sellers against two other groups of sellers, who are investors and institutions. Individual sellers are owner-occupiers, who live in the houses that have the same addresses as the transacted houses. Investor sellers are those whose current home addresses are different from the addresses of transacted house. As we use only housing transactions in the resale market in the tests, developers’ sales in the primary market are excluded. The institutional sellers in the resale samples include only firms that sell houses that are no longer occupied by their foreign executives.

Compared to investor sellers, individual sellers driven by mobility motive are more likely to be under pressure to sell their houses quickly in order to move into new houses. We derive three binary dummy variables, [k_i = (“individuals”, “investors” and “institutions”)], which have a value of either 0 or 1, to represent the three groups of sellers, respectively; and use the sellers’ dummy (k_i) as the dependent variables in the following OLS regression controlling for the district and the time fixed effects:

$$k_i = \alpha + \beta \times \text{Agent}_{it} + \gamma \mathbf{X}_i + \mu_d + \varphi_t + \varepsilon_{itd} \quad (3)$$

*** Insert Table 8 about here ***

We exclude developers’ sales from the sample used to estimate the selection models in Equation (3). The OLS results with the three different binary seller variables as dependent variables are summarized in Table 8. The first three models (Columns 1-3) use the resale housing sample, and

the last model (Columns 4) excludes “institutions” (firm sellers) from the sample in the estimations. The results show that the coefficients on the “Agent” dummy are positive, but insignificant in the “individuals” (Column 1) and “investors” (Column 2) models. The 95% confidence interval of the coefficient in column 1 is [-0.5%, 4.8%]. The coefficient is negative but insignificant in the “institutions” model (Column 3). The results though show that agents are more likely to buy houses from individual sellers and investors, and they are less likely to buy houses from firms. However, the selection channel is not statistically significant in the models. When we exclude “institutions” sellers from the samples, the coefficient on the “Agent” variables is still not significant (Columns 4). We find no evidence to suggest that real estate agents “cherry pick” a specific group of buyers when buying their own houses. Therefore, the hypothesis that agent-buyers’ use information advantages to self-select houses when buying for their own use is not supported .

We conduct further tests on the “cherry picking” channel using the second proxy for “weak” sellers. We use sellers who are involved in lawsuits to represents the group that is under time pressure to sell their houses. This group shares some characteristics of “financially distressed” sellers, who are forced to sell their houses in a short time at “fire sale” prices. We first merge the law event dataset into the housing transaction dataset, and identify sellers, who are involved in law events relating to bankruptcy, car accident, sales of goods, credit card, and tenancy disputes. We define this group of sellers as the “treatment” group by a “lawsuits” dummy, which has a value of 1, if a seller is involved in one of the law events; and 0 otherwise. We use five different indicators to separately identify the law events, (ι_i) , and substitute the seller indicators (k_i) in Equation (3) by the new set of “lawsuit” indicators for the sellers, (ι_i) , to test if agents’ selection for a particular group of sellers is observed.

*** Insert Table 9 about here ***

The OLS models with the “lawsuits” dummy variables as dependent variables are estimated using the resale housing sample for the period from 1995 to 2012. We test if agents are more likely to buy houses from sellers with a specific type of lawsuits, such as bankruptcy (Column 2), car accident (Column 3), or sales of goods (Column 4), or credit card (Column 5), and tenancy (Column 6). “Institutions” that are not found in our law events dataset are excluded in our analyses. The results are reported in Table 9. The coefficients on the “Agent” dummy are insignificant in all the models indicating that there is no causal relationship between the “fire sale” sellers and the agent-buyers. The 95% confidence interval of the coefficient in column 1 is [-0.6%, 1.6%]. There is no evidence suggesting that agents are more likely to buy houses from sellers involved in lawsuits. The results are consistent, when we split the law events into different categories as in Columns 2 to 6. The results do not support the “cherry picking” story that agents are expected to exploit information advantages to buy their own houses from sellers involved in different law events.

One concern is that although we cannot reject a coefficient of zero, we cannot reject a positive coefficients on cherry picking. For example, in Table 8 Column 1, we can reject that the coefficient is larger than 4.8% at the 5% level. The question is whether the positive coefficients are large enough to explain the agent discount. We analyze the relationship between housing price and weak sellers and report the results in Table 10.

*** Insert Table 10 about here ***

The dependent variable is log-unit sale price (\$ per square meter) of houses. “Weak Seller” is a dummy variable that has a value of 1 if the seller is involved in lawsuits (column 1 and 2) or is an individual seller (column 3 to 6). We find that houses sold by weak sellers are cheaper. Houses sold by sellers involved in lawsuits are 3.5% cheaper and those sold by individual sellers are 9.6% cheaper. Thus cherry picking individual sellers can explain at most 0.46% (=4.8% x 9.6%) of agent discount and cherry picking sellers involved in lawsuits can explain at most 0.06% (=1.6% x 3.5%). Therefore, even if there are some cherry picking, the effect is unlikely to explain the observed 2% agent discount.

In summary, there is no evidence that agent-buyers are more likely to buy houses from the two types of weak sellers: individual sellers or sellers involved in lawsuits. Our results do not support the hypothesis that real estate agents use information advantages to “*cherry pick*” weak sellers in the market.

4.3.2. Bargaining Power of Agents

The second possible explanation is that real estate agents use information advantages to tilt their bargaining power against weak sellers. We test the bargaining power channel by estimating the extended log-price models by adding an interactive term, (“Agent_{it} x k_j”), as below:

$$\ln(P_{i,d,t}) = \alpha + \beta \times \text{Agent}_{it} + \sum_{j=1}^2 \theta_j \times (\text{Agent}_{it} \times k_j) + \sum_{j=1}^2 \delta_j \times k_j + \gamma \mathbf{X}_i + \mu_d + \varphi_t + \varepsilon_{itd} \quad (4)$$

A negative coefficient on the interaction term (Agent_{it} x k_j) implies that agents receive larger discounts when buying houses from weak sellers. The result, if significant, is consistent with the bargaining power explanation. We use the same two sellers’ characteristics as proxies for weak sellers: individual sellers and sellers involved in lawsuits.

Based on the first proxy, we identify individuals (owner occupiers) as the “weak” sellers who face liquidity constraints in their housing mobility decisions. Given that they lived in the same houses that they sold, they were under pressure to sell their existing houses in the shortest possible time, so that they could use the proceeds to pay for their new houses. For investors, who usually own multiple houses in their portfolios, they would have no such time pressure in selling

their houses. Investors are “strong” negotiators and also more informed about housing price trends. Their exit strategies are mainly motivated by investment returns. “Institutions” are not liquidity constrained sellers, but they buy houses to provide residences as part of the perks for their top foreign executives. They will sell the houses quickly, when the houses are no longer needed for for their foreign executives, so that they could plough back proceeds from housing sales into the firms for other operational needs. Firms would not usually haggle on selling prices, as long as they are able to recover the costs after depreciation from the sales. Based on the characteristics of the sellers, we hypothesize that individual and institutional sellers are under time pressure to sell their houses, compared to investors, who could wait for the right prices before selling their houses. Therefore, individuals and institutions will have weaker bargaining power relative to investors when selling their houses in the market.

*** Insert Table 11 about here ***

The results for the models as defined in Equation (4) are shown in the first three columns of Table 11. Using “individuals” as the base in Columns (1) and (2), we find that the agents’ price advantages are significant when they transact with individual sellers. For transactions involving individual sellers, real estate agents buy their own houses for prices that are 2.09% lower than comparable houses bought by non-agent buyers. The coefficients on “institutions” (Columns 1 and 2) and “investors” (Column 2) are positive indicating that houses bought from institutional sellers and investors (controlling for buyers’ characteristics) are higher relative to houses bought from individuals. When we interact the “Agent” with the two sellers’ dummies (“institutions” and “investors”) (with the individual sellers as the reference), we find that the coefficients on the “Agent×Institutions” are negative at -1.60% (Column 1) and -1.60% (Column 2) after controlling for buyers’ characteristics. The coefficients on “Agent×Investors” are positive at 0.99% and 1.73% for the base model (Column 1) and the model with controlled socioeconomic variables (Column 2), respectively, but the results are statistically insignificant. The results imply that while agents enjoy 2.09% discounts when buying houses from individual sellers, they enjoy larger discounts when buying houses from institutional sellers. However, no significant discounts are found in the transactions involving investor sellers. When we exclude institutional sellers from the samples and re-estimate the model in Column 3, the results are consistent with the earlier results in Columns 1 and 2.

In summary, our results suggest that agent buyers do enjoy more discounts when buying houses from “individuals” and “institutions” relative to “investors”. The information advantages could be translated into average price discounts of 2.09% for houses sold by individuals to agent-buyers. Firms that are motivated to liquidate houses in the shortest possible time have the weakest bargaining power in the transactions. Agents are able to reduce prices by further 1.60% when buying houses from firms (“institutions”). Investors’ bargaining position is relatively stronger as reflected in the results that show no price discounts for housing transactions between

agents and investors. The results are consistent with the bargaining power explanation that agents use information advantages to tilt their bargaining power against individuals and institutional sellers, such that they pay lower prices for comparable houses than other non-agent buyers.

Based on the second proxy of the weak sellers who involved in lawsuits, we estimate the log-unit price models as in Equation 4 by replacing the seller identity k_i by the “lawsuits” dummy denoting sellers involved in lawsuits. These sellers are synonymous to “distressed” sellers, who are under pressure to sell their houses in the shortest possible time. The results are summarized in Table 12. The results in Column (1) show that the “Agent” coefficient is significant at -2.05%, which indicates that agents could exploit their information advantages by paying lower prices when buying own houses from average sellers without lawsuits. The “lawsuits” dummy that is also significant at -3.40% indicating that sellers with lawsuits suffered even greater discounts when selling their houses. The results are consistent with the “fire sales” cases. However, the interactive term “Agent×Lawsuits” is not significant in the model, which shows no price differences between agent-buyers and non-agent buyers, when they buy houses from the “distressed” sellers.

*** Insert Table 12 about here ***

The earlier model does not control the sequence of the law events and the housing transactions. The results could be biased downward, if we do not differentiate housing sales by sellers that occur before the law events from those sold under “fire sale” conditions after the law events. We define two time dummies – “Before Lawsuits” that has a value of 1, if a housing transaction takes place before the seller of the house is convicted in a law event; or 0 otherwise; and “After Lawsuits” that has a value of 1, if a housing transaction takes place on or after the date of a law event convicted by the seller; or 0 otherwise. We rerun the log-price model and report the results in Column 2 of Table 12. Our results show that the “Agent” coefficient is still significant at -2.05%; and the two time dummy variables “Before Lawsuits” and “After Lawsuits” are also significant at -3.27% and -4.14%, respectively. When we interact the two time dummies with the “Agent”, we find interestingly that the coefficients on the two interactive terms have opposite signs. The coefficient of 6.60% on the “Agent×Before Lawsuits” variable indicates that Agents enjoy smaller discounts when buying own houses from sellers, before they were implicated in lawsuits. However, when Agents bought houses from distressed sellers after the law events, agent-buyers enjoy a larger discount of 8.56% compared to buying from normal sellers.

We truncate transactions that occur outside a 3-year window before and after law events to minimize possible distortions caused by other unobserved extraneous factors. The results based on the truncated sample are shown in Column 3 of Table 12, and they are largely consistent with the earlier results in Column 1 of Table 12. The results imply that agents with the *ex-post* knowledge of sellers’ involvement in law events exploit the information advantages to buy

houses for their own use at lower prices from these sellers, compared to the cases where houses are bought by non-agent buyers, who do not have the privity to sellers' lawsuit information. The positive price effects before law events indicate that agents do not have prior knowledge of sellers' conditions, and could not exploit information advantages in the negotiations. However, after law events are revealed *ex-post*, agent-buyers use the information advantages to tilt bargaining power against the distressed sellers, when buying houses for their own use

In the main model, we aggregate all the lawsuits using a dummy variable "Lawsuits" in our log-pricing models on the assumption that there is no heterogeneity in different types of law events. We sort the events by type into five different categories including car accident, sale of good, credit card, tenancy and bankruptcy, using five different binary indicators denoted by (φ_i) , and define the "Before Lawsuits $|\varphi_i$ " and "After Lawsuits $|\varphi_i$ " time dummies, which indicate the timing of housing transactions either before or after sellers were convicted in lawsuit φ_i . We run the log-unit housing price model using only resale housing transactions for the full sample periods, and the results are summarized in Table 13. We also run the regressions using only the six years truncated sample period that is 3 years before and 3 years after the occurrence of the law events. The results are largely robust and consistent, and the results based on the truncated sample period are not included in the paper.

*** Insert Table 13 about here ***

The results show that information advantages story is supported by the coefficient on "Agent", which is highly significant with the price discounts estimated in the range between 2.09% and 2.16%. The coefficients on "Before Lawsuits" are not significant, except in the "Bankruptcy" model (Column 1), which show significant and negative coefficient. The coefficients on "After Lawsuits" are significant and negative in the lawsuit models involving credit card (Column 4), tenancy (Column 5) and bankruptcy (Column 1). The results show that buyers are not able to exploit information advantages against sellers before the occurrence of the lawsuit events (except for bankruptcy). However, when the lawsuits are known *ex-post*, only in cases involving credit card, tenancy and bankruptcy disputes, sellers were found to be under pressure to sell their houses at discounts in the markets. When we interact the two time dummies with "Agent", we find that in most cases except in the bankruptcy events, buyers are not able to exploit information advantages to buy houses at cheaper prices relative to other buyers before and after the law events. We find that buyers, who know *ex-post* about sellers' bankruptcy events, are able to use their information advantages to buy houses for their own use at significant discounts relative to other non-agent buyers ("Agent \times After Lawsuits"). However, prior to the law events, we find that agent-buyers pay higher prices for comparable houses than other ("Agent \times Before Lawsuits").

In summary, we find that *ex-post* knowledge of sellers' law events (information advantages) give agents bargaining advantages against the sellers, such that they are able to buy houses for their

own use at lower prices from the affected sellers compared to other non-agent buyers.¹² Our results support the bargaining channel, which indicates that agents exploit their information advantages to tilt the bargaining power in their favor against “weak” sellers when buying houses for their own use.

4.4. *Discussions about other Alternative Explanations*

Agents could have engaged in the flipping activities, where they buy houses and quickly sell them for profit in the market, is a possible alternative explanation to our story of buying house for their own use. The flipping story implies that there would be a large volume of selling activities by agents, if agents could buy houses at discounted prices and sell them in short time to make investment gains. However, we find no evidence to suggest that the flipping is likely to be the main story in our study. First, only 8.1 percent of the housing sales were on houses previously bought by the agent buyers. Second, in Table 6 we show that the establishment of CEA in 2010 reduce the agent discount. If the agent discount is due to flipping and agents pick low quality houses to buy, there should be no effect of CEA and we should observe a persistent agent discount before and after the establishment of CEA. Third, we test if the agent buyers, who are identified as investors (based on the matches between their current home addresses and transacted house addresses), enjoy larger discounts than agent-buyers, who buy houses for their own occupation purposes. Owner occupiers are individuals, whose current home addresses are the same as the addresses of transacted houses. We include an interactive term (“Agent×Investor”), where the “Investor” dummy variable has a value of 1, if buyers are investors; or 0 otherwise, in the log unit housing price models, and the results are summarized in Table 14.

*** Insert Table 14 about here ***

We find that when the agent-buyers are not investors, agents pay 2.1% lower in prices for comparable houses compared other non-agent buyers. The coefficients on the “Agent×Investor” term are not significant. This indicates that when agents are investors, they enjoy the discounts as agent-buyers, who are owner occupiers. Our results do not support the flipping story as the main reasons for the price discounts in agent-buyers’ transactions.

Another alternative explanation of the agents’ discounts is that agents time the market to earn larger price discounts when buying houses for their own use. The market timing story, if not rejected, implies that agents’ transactions are expected to bunch around a selected time in a year, during which agents can enjoy larger discounts when buying houses. We provide the following evidence to suggest that the market timing story is likely to drive the agents’ information advantage story in our study. Figure 4, Panel B shows that agents’ housing transactions are

¹² As agents buy houses for their own occupations, they are not likely to have more time advantage in waiting for luck of getting a lower offer price accepted in a transactions than other buyers.

distributed with a narrow range of between 5 percent and 5.6 percent across the 12 months. Bunching of agents' transactions is not evidenced in the data, and the differences in the fraction of agents' transactions by month are not significant ($p=0.71$). We also explore the month effects in agent discounts by interacting the agent indicator with various time-related indicators, which include the month of year, the quarter of year, the 3-month SIBOR, and the housing price index.¹³

*** Insert Table 15 about here ***

Table 15 presents the results. In column (1), we analyze the heterogeneous effects of agents' discounts by month, and find that the agent discounts are smaller in the months of June, November and December. However, the coefficients on the interaction term are not significant. Since there is no bunching of agent transactions in different months, we could not support the story that agents choose a good month in a year to buy houses. In column (2), we analyze the heterogeneous effects of agents' discounts by interacting with the 3-month SIBOR, which is a proxy of cost of borrowing. We also analyze the heterogeneous effects of agents' discounts by interacting with housing price index in Singapore; and the results as in column (3) show that the coefficients on the interaction terms are not significant. In summary, there is no evidence that agents choose a good timing to buy houses based on various strategies, which include either by a month in a year, by mortgage costs, or by housing price.

Another alternative explanation of the agents' discounts is that agent don't bundle sellers' appliances into the house when they purchase it, so they are buying less quantity. In the setting of Singapore, like any buyers, agent buyers are also expected to take possession of houses without encumbrance. Sellers' private properties such as appliances and equipment, which are not considered as immovable fixtures, are not bundled in most of the housing transactions in Singapore. Thus, it is unlikely to explain the observed agent price discounts.

5. Conclusion

This paper extends the earlier empirical studies on information advantages and market distortion in real estate brokerage industry using Singapore's real estate market data. We merge multiple datasets on registered real estate agents (salespersons), law events, personal details and current home addresses into a dataset containing more than 100,000 private non-landed housing transactions in Singapore for the periods from 1995 to 2012. With this unique dataset on the

¹³ 3 month Singapore Interbank Overnight Rate (SIBOR) is usually the index rate for home mortgage in Singapore. We use price index of non-landed properties from Urban Redevelopment Authority (URA) as our housing price index.

buy-side activities, we empirically test information advantages in real estate brokers/agents, which contribute differently to the earlier evidence in the US that use data in the sale-side activities. We find significant evidence to suggest that real estate agents do exploit information advantages to buy houses for their own use at prices that are about 2% lower than comparable houses bought by non-agent buyers. We conduct various robustness tests using the repeated sales sample and the matched samples derived using the propensity score matching technique, and the results are consistent and robust.

On 22 October 2010, the Singaporean government introduced a new regulatory regime to the real estate brokerage market via the establishment of a new statutory board known as the Council for Estate Agencies (CEA) under the Estate Agency Act (Chapter 95A). We use the policy event to set up a natural experiment to test if agents' exploitation of information advantages in obtaining discounts in prices for houses bought for their own use were curtailed after CEA has come into operation. The results in our *diff-in-diff* tests show that the agents' discounts in housing prices when agents buy houses for their own use before the CEA regime have significantly decreased in the post-CEA regime. It seems like agents are no longer able to exploit information advantages to buy houses for their own use at lower prices compared to other non-agent buyers.

Why do real estate agents pay lower prices for houses bought for their own use? We probe into two possible channels via which agents could exploit their information advantages. First, we argue that agents could use their information advantages to "cherry pick" houses from a selected group of sellers. Second, they use information advantages to tilt the bargaining power against weaker sellers, and pay lower prices for houses bought for their own use from these sellers.

We use two identification strategies to sort the sellers into two groups: a group of sellers with "weak" bargaining power, and another group of sellers, who are not under time pressure to quickly sell their houses. Like in the "fire sale" condition, we assume that financially distressed sellers are forced to sell their assets in the shortest possible time and at prices that are below the market (intrinsic) values. These sellers are in a weak bargaining position to ask for high selling prices. In the first identification strategy, we divide sellers into three groups, which include institutions, individuals, and investors. For Individuals who are also owner occupiers, they live in the same house as the house sold in the market; whereas, investors hold more than one house for investment purposes. Individuals, who sell their houses for mobility motives, are likely to face time pressure to sell their houses quickly before moving into their new houses. Similarly, firms (institutions) are also more likely to sell houses, which have been bought as part of the residency perks for foreign top executives, when the houses are no longer required. Therefore, we identify individuals and institutions in our experiments as the groups, which face time pressure to sell their houses, and investors are the tougher bargainers in the housing markets.

When we run our regressions using the binary seller type indicators as dependent variables, we

find no significant relationships between the agent-buyers and the seller type in the transactions. There is no evidence to suggest that agents exploit information advantages to cherry pick houses from the weak sellers. However, when we test price variation in housing transactions between agents and different seller groups, we find strong evidence that agents pay lower prices when they buy their own houses from “individuals” and “institutions”, but no price discounts are found in houses bought from investors. We could not rule out the bargaining power story that agents use information advantages to bargain prices down when they buy houses from the “weaker” sellers.

In our second identification strategy, we identify sellers, who are involved in various lawsuits (bankruptcy, car accidents, sales of goods, credit card and tenancy disputes) as the group of sellers facing time pressure to sell their houses. We run the selection models using the binary lawsuit indicators as the dependent variables, and find no evidence that agent-buyers are more likely to buy houses from sellers affected by the lawsuits compared to other non-agent buyers. However, we could not reject the bargaining power story because we find significant discounts in houses bought by agent-buyers given that they have ex-post knowledge of the law events of the sellers. The results make useful contributions to the literature showing that real estate agents with special knowledge could tilt the bargaining power to their favor and cause price distortion in the market.

Reference:

Allen, Marcus T., Rutherford, Jessica, Rutherford, Ronald, and Yavas, Abdullah, 2016. Conflicts of Interest in Residential Real Estate Transactions: New Evidence. *Paper presented at the ASSA-AREUEA Conference*, San Francisco, California, January 3-6, 2016.

Bailey, EE, and WJ Baumol, 1983. Deregulation and the theory of contestable markets. *Yale Journal on Regulation*, 1:111-137.

Barwick, Panle Jia and Parag A. Pathak, 2011. The cost of free entry: an empirical study of real estate agents in Greater Boston. National Bureau of Economic Research working paper 17227.

Bernheim, Douglas and Jonathan Meer, 2013. Do real estate brokers add value when listing services are unbundled? *Economic Inquiry*, 51 (2): 1166-1182.

Campbell, John Y., Stefano Giglio and Parag Pathak, 2011. Forced Sales and House Prices. *American Economic Review*, 101(5): 2108-31.

Hendel, Igal, Aviv Nevo and François Ortalo-Magné 2009. The Relative Performance of Real Estate Marketing Platforms: MLS versus FSBOMadison.com. *American Economic Review*, 99(5): 1878-98.

Gabaix, Xavier and David Laibson, 2006. Shrouded Attributes, Consumer Myopia, and Information Suppression in Competitive Markets. *The Quarterly Journal of Economics*, 121 (2): 505-540

Garmaise, Mark J. and Tobias J. Moskowitz, 2004. Confronting Information Asymmetries: Evidence from Real Estate Markets. *Review of Financial Studies*, 17(2): 405-37.

Hsieh, Chang-Tai and Enrico Moretti, 2002. Can free entry be inefficient? Fixed commissions and social waste in the real estate industry. National Bureau of Economic Research working paper 9208.

Levitt, S. and Chad Syverson, 2008a. Antitrust Implications of Home Seller Outcomes when using Flat-Fee Real Estate Agents. Brookings-Wharton Papers on Urban Affairs.

Levitt, S. and Chad Syverson, 2008b. Market Distortions when Agents are Better Informed: The Value of Information in Real Estate Transactions. *Review of Economics and Statistics*, Vol. 90 pp. 599–611.

Rutherford, Ronald, Thomas Springer and Abdullah Yavas, 2005. Conflicts between principals and agents: Evidence from residential brokerage. *Journal of Financial Economics*, Vol. 76(3), 627-665

Stein, Jeremy, 2005. Why Are Most Funds Open-End? Competition and the Limits of Arbitrage, *Quarterly Journal of Economics*, 120(1): 247-272.

Table 1: Descriptive Statistics

Sample	Total	Agent-Buyer	Non-Agent-Buyer
Panel A: Original Sample			
Price (Singapore dollars per square meter)	8245.5800	8127.0000	8252.2400
Size (square meters)	120.2209	116.5815	120.4254
Floor	0.7203	0.7108	0.7208
Condominium	0.8869	0.8860	0.8869
Freehold	0.4359	0.3952	0.4382
Newsale	0.5407	0.5051	0.5427
Resale	0.3791	0.4059	0.3776
Male	0.6154	0.5302	0.6202
Chinese	0.9391	0.9635	0.9377
Marriage	0.5987	0.6536	0.5957
Age	43.2279	40.3205	43.3915
Total observation	108,534	5,775	102,759
Panel B: Propensity Score Matched Sample			
Price (Singapore dollars per square meter)	8190.4800	8122.9900	8257.9700
Size (square meters)	115.6771	116.6108	114.7434
Floor	0.7143	0.7109	0.7176
Condominium	0.8935	0.8856	0.9015
Freehold	0.3917	0.3950	0.3884
Newsale	0.5113	0.5052	0.5175
Resale	0.4024	0.4066	0.3982
Male	0.5304	0.5306	0.5303
Chinese	0.9634	0.9637	0.9632
Marriage	0.6556	0.6536	0.6576
Age	40.3698	40.3577	40.3819
Total Observations	11,402	5,701	5,701

Note: This table presents the aggregate-level summary statistics of our dataset before and after Propensity Score matching. The full sample includes 108534 property transactions of condominium and apartment in Singapore from 1995 to 2012. Propensity score matching are one-to-one match by setting agent as treatment group based on the property information, transaction year, location of property (district level) and other buyer characteristics. Panel A reports the summary statistics for the full sample, and Panel B reports the summary statistics for propensity score matched sample. “Price” is the unit sale price in Singapore dollars per square meter. “Size” is the transacted property size in square meters. “Floor” is the floor level of the property. “Condominium” has a value of 1, if a condominium is purchased; and 0 otherwise indicates an apartment. “Freehold” has a value of 1, if a house has a freehold tenure; and 0 otherwise. “Newsale” represents houses sold by developers in the primary market. “Resale” represents houses sold in the secondary market. “Male” has a value of 1 for a male buyer, 0 otherwise for a female buyer. “Chinese” identifies Chinese buyers, and 0 otherwise identifies other races (Malay, India and Others). “Marriage” has a value of 1 for a married buyer; and 0 otherwise. “Age” measures the buyer’s age.

Table 2: Information Advantages of Real Estate Agents

Sample:	All Samples		Repeat sale		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Model						
Agent	-0.0199*** (0.0029)	-0.0188*** (0.0029)	-0.0157*** (0.0049)	-0.0148*** (0.0051)	-0.0171*** (0.0039)	-0.0166*** (0.0039)
Size (square meters)	-0.0011*** (0.0000)	-0.0011*** (0.0000)	-0.0030*** (0.0007)	-0.0030*** (0.0007)	-0.0016*** (0.0001)	-0.0017*** (0.0001)
Condominium	0.0965*** (0.0017)	0.0970*** (0.0017)	-0.0472 (0.0541)	-0.0475 (0.0542)	0.1122*** (0.0052)	0.1119*** (0.0052)
High Floor	0.0396*** (0.0014)	0.0398*** (0.0014)	0.0172** (0.0077)	0.0156** (0.0078)	0.0348*** (0.0041)	0.0349*** (0.0041)
Freehold	0.1300*** (0.0017)	0.1300*** (0.0017)	0.0166 (0.0690)	0.0159 (0.0691)	0.1169*** (0.0051)	0.1165*** (0.0051)
Newsale	0.0200*** (0.0026)	0.0197*** (0.0026)	-0.0253** (0.0102)	-0.0260** (0.0103)	0.0170** (0.0076)	0.0168** (0.0076)
Resale	-0.2068*** (0.0026)	-0.2075*** (0.0026)	-0.0585*** (0.0127)	-0.0617*** (0.0129)	-0.1945*** (0.0077)	-0.1944*** (0.0077)
Intercept	9.2985*** (0.0118)	9.3018*** (0.0122)	9.7696*** (0.2375)	9.3018*** (0.0122)	9.3132*** (0.0345)	9.3052*** (0.0362)
Socioeconomic Variables	No	Yes	No	Yes	No	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
House Fixed Effects	No	No	Yes	Yes	No	No
Observations	108,534	107,399	2,874	2,831	11,402	11,402
R-Squared	0.7673	0.7674	0.9518	0.9522	0.7806	0.7810

Note: This table shows results of OLS regression analysis. The dependent variable is log-unit sale price (\$ per square meter) of houses. “Agent” is dummy variable that has a value of 1, if a buyer is also an agent; and 0 otherwise. The control variables in the model include unit size (sqm), a dummy on condominium, a dummy on high floor that identifies unit located at level 9 and above, a dummy on new sale and a dummy on resale. Models in Column 2, 4 and 6 also control for social-economic variations using the buyer characteristics, such as dummies on “Male”, “Chinese”, and “Marriage”. For age, we use a dummy on “Old Age” that takes a value of 1, if a buyer is 60 year and older; and zero otherwise. The district fixed effect, which is represented by the 28 planning districts, and the transaction year fixed effects are included in the regression. For Columns 3 and 4, housing fixed effects are included. Standard errors are reported in parenthesis. Regression results in Columns 1 and 2 are estimated using the full sample observations. Columns 3 and 4 are estimated using repeated sale samples, i.e. houses sold more than one time during the sample period, and where one of the buyer was an agent. Columns 5 and 6 are estimated based on matched samples generated using the Propensity Score Matching approach.

*Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Table 3: Selection of Agents from Samples of Agents-Buyers with Multiple Matched Names

Agent dummy selection Sample Model	Include all agents with multiple matching names				Randomly select one out of agents with multiple matching names			
	Full Sample		PSM Sample		Full Sample		PSM Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agent	-0.0131*** (0.0022)	-0.0132*** (0.0023)	-0.0094*** (0.0029)	-0.0093*** (0.0029)	-0.0172*** (0.0026)	-0.0163*** (0.0027)	-0.0136*** (0.0036)	-0.0133*** (0.0036)
Size (square meters)	-0.0011*** (0.0000)	-0.0011*** (0.0000)	-0.0016*** (0.0000)	-0.0016*** (0.0000)	-0.0011*** (0.0000)	-0.0011*** (0.0000)	-0.0016*** (0.0000)	-0.0016*** (0.0000)
Condominium	0.0966*** (0.0017)	0.0970*** (0.0017)	0.1095*** (0.0039)	0.1093*** (0.0039)	0.0965*** (0.0017)	0.0970*** (0.0017)	0.1053*** (0.0049)	0.1051*** (0.0049)
High Floor	0.0398*** (0.0014)	0.0399*** (0.0014)	0.0349*** (0.0030)	0.0349*** (0.0030)	0.0396*** (0.0014)	0.0398*** (0.0014)	0.0364*** (0.0038)	0.0364*** (0.0038)
Freehold	0.1301*** (0.0017)	0.1301*** (0.0017)	0.1322*** (0.0039)	0.1321*** (0.0039)	0.1300*** (0.0017)	0.1300*** (0.0017)	0.1285*** (0.0048)	0.1285*** (0.0048)
Newsale	0.0201*** (0.0026)	0.0197*** (0.0026)	0.0090 (0.0057)	0.0088 (0.0057)	0.0201*** (0.0026)	0.0197*** (0.0026)	0.0145 (0.0071)	0.0145 (0.0071)
Resale	-0.2070*** (0.0026)	-0.2076*** (0.0026)	-0.2013*** (0.0059)	-0.2014*** (0.0059)	-0.2069*** (0.0026)	-0.2075*** (0.0026)	-0.1994*** (0.0073)	-0.1995*** (0.0073)
Intercept	9.2985*** (0.0118)	9.3016*** (0.0122)	9.3240*** (0.0287)	9.3178*** (0.0305)	9.2985*** (0.0118)	9.3018*** (0.0122)	9.3368*** (0.0346)	9.3402*** (0.0363)
Socioeconomic Variables	No	Yes	No	Yes	No	Yes	No	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	108,534	107,399	20,154	20,154	108,534	107,399	13,426	13,426
R-Squared	0.7673	0.7674	0.7764	0.7765	0.7673	0.7674	0.7772	0.7774

Note: The dependent variable is log-unit sale price (\$ per square meter) of houses. "Agent" is dummy variable that has a value of 1, if a buyer is also an agent; and 0 otherwise. In the left-hand Panel (Columns 1 to 4), we include all agents with multiple matched names in our samples; whereas in the right-hand Panel (Columns 5-8), we randomly select only one agent from the sample of agents with multiple matched names. Standard errors are reported in parenthesis. The matched samples in Columns 3, 4, 7 and 8 are generated using the Propensity Score Matching approach. *Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Table 4: Heterogeneity Tests by Housing Type

Sub-market Model	Resale Market		Newsale Market	
	(1)	(2)	(3)	(4)
Agent	-0.0220*** (0.0050)	-0.0215*** (0.0051)	-0.0160*** (0.0036)	-0.0144*** (0.0036)
Size (square meters)	-0.0014*** (0.0000)	-0.0014*** (0.0000)	-0.0008*** (0.0000)	-0.0008*** (0.0000)
Condominium	0.1862*** (0.0030)	0.1866*** (0.0030)	0.0344*** (0.0022)	0.0348*** (0.0022)
High Floor	0.0410*** (0.0025)	0.0408*** (0.0025)	0.0384*** (0.0017)	0.0387*** (0.0017)
Freehold	0.1416*** (0.0029)	0.1415*** (0.0029)	0.1224*** (0.0022)	0.1224*** (0.0022)
Intercept	9.0517*** (0.0169)	9.0449*** (0.0175)	9.3946*** (0.0203)	9.3969*** (0.0208)
Socioeconomic Variables	No	Yes	No	Yes
Spatial Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	41,141	40,737	58,687	58,071
R-Squared	0.7097	0.7095	0.8024	0.8027

Note: This table shows results of OLS regression analysis. The dependent variable is log-unit sale price (\$ per square meter) of houses. “Agent” is dummy variable that has a value of 1, if a buyer is also an agent; and 0 otherwise. The control variables in the model include unit size (sqm), a dummy on condominium, a dummy on high floor that identifies unit located at level 9 and above, a dummy on new sale and a dummy on resale. Standard errors are reported in parenthesis. Regression results in Columns 1 and 2 are estimated using resale samples; whereas Columns 3 and 4 are estimated using new sale samples.

*Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Table 5: Heterogeneity Tests by Firm Size

Firm Size Dummy:	(i) Agency firms with 100 or less agents		(i) The Top 5 largest agency firms by employee number	
	(1)	(2)	(3)	(4)
Agent	-0.0185*** (0.0061)	-0.0181*** (0.0062)	-0.0202*** (0.0044)	-0.0191*** (0.0044)
Firm Size	0.0032 (0.0046)	0.0047 (0.0047)	0.0019 (0.0053)	0.0038 (0.0054)
Agent×Firm Size	-0.0013 (0.0083)	-0.0036 (0.0084)	-0.0024 (0.0078)	-0.0042 (0.0079)
Size (square meters)	-0.0011*** (0.0000)	-0.0011*** (0.0000)	-0.0011*** (0.0000)	-0.0011*** (0.0000)
Condominium	0.0965*** (0.0017)	0.0970*** (0.0017)	0.0965*** (0.0017)	0.0970*** (0.0017)
High Floor	0.0396*** (0.0014)	0.0398*** (0.0014)	0.0396*** (0.0014)	0.0398*** (0.0014)
Freehold	0.1300*** (0.0017)	0.1300*** (0.0017)	0.1300*** (0.0017)	0.1300*** (0.0017)
Newsale	0.0200*** (0.0026)	0.0197*** (0.0026)	0.0200*** (0.0026)	0.0197*** (0.0026)
Resale	-0.2069*** (0.0026)	-0.2075*** (0.0026)	-0.2069*** (0.0026)	-0.2075*** (0.0026)
Intercept	9.2985*** (0.0118)	9.3018*** (0.0122)	9.2989*** (0.0118)	9.3018*** (0.0122)
Socioeconomic Variables	No	Yes	No	Yes
District Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	108,534	107,399	108,534	107,399
R-Squared	0.7673	0.7674	0.7673	0.7674

Note: This table shows results of OLS regressions that control for large agency firm effects. The dependent variable is logarithm of unit price per square meter. We use two definition of “Firm Size” dummies in the regressions. Columns 1 and 2 represent agency firms with 100 or less agents; and Columns 3 and 4 exclude the 5 largest agency firms by the number of agents hired. “Agent” is dummy variable that has a value of 1, if a buyer is also an agent; and 0 otherwise. The control variables in the model include unit size (sqm), a dummy on condominium, a dummy on high floor that identifies unit located at level 9 and above, a dummy on new sale and a dummy on resale. We control for social-economic variations in Columns 2 and 4 using the buyer characteristics, such as dummies on “Male”, “Chinese”, and “Marriage”. For age, we use a dummy on “Old Age” that takes a value of 1, if a buyer is 60 year and older; and zero otherwise. The district fixed effect, which is represented by the 28 planning districts, and the transaction year fixed effects are included in the regression.

*Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Table 6: Effects of the New Regulatory Regime

	<u>Full Samples</u>		<u>2005 - 2012</u>	<u>Newsale</u>	<u>Resale</u>
	(1)	(2)	(3)	(4)	(5)
Agent	-0.0209*** (0.0030)	-0.0197*** (0.0030)	-0.0214*** (0.0041)	-0.0150*** (0.0037)	-0.0233*** (0.0054)
Agent × AfterCEA	0.0149 (0.0116)	0.0143 (0.0117)	0.0157 (0.0123)	0.0216 (0.0224)	0.0164 (0.0159)
Size	-0.0011*** (0.0000)	-0.0011*** (0.0000)	-0.0009*** (0.0000)	-0.0008*** (0.0000)	-0.0014*** (0.0000)
Condominium	0.0965*** (0.0017)	0.0970*** (0.0017)	0.0769*** (0.0022)	0.0348*** (0.0022)	0.1866*** (0.0030)
High Floor	0.0396*** (0.0014)	0.0398*** (0.0014)	0.0510*** (0.0019)	0.0387*** (0.0017)	0.0408*** (0.0025)
Freehold	0.1300*** (0.0017)	0.1300*** (0.0017)	0.0959*** (0.0023)	0.1225*** (0.0022)	0.1415*** (0.0029)
Newsale	0.0200*** (0.0026)	0.0196*** (0.0026)	0.0579*** (0.0031)		
Resale	-0.2069*** (0.0026)	-0.2075*** (0.0026)	-0.1954*** (0.0032)		
Intercept	9.2980*** (0.0118)	9.3013*** (0.0122)	9.2635*** (0.0145)	9.3965*** (0.0208)	9.0441*** (0.0176)
Socioeconomic Variables	No	Yes	Yes	Yes	Yes
Spatial Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	108,534	107,399	63,580	58,071	40,737
R-Squared	0.7673	0.7674	0.7629	0.8027	0.7095

Note: This table shows results of OLS regression analysis. The dependent variable is log-unit sale price (\$ per square meter) of houses. “AfterCEA” is a time dummy that represents the establishment of Council for Estate Agencies (CEA) on 22 October 2010, and it has a value of 1, if a transaction occurs on and after 22 October 2010; and 0 otherwise. “Agent” is dummy variable that has a value of 1, if a buyer is also an agent; and 0 otherwise. The control variables in the model include unit size (sqm), a dummy on condominium. Socioeconomic variations are controlled in Columns 2-5 using the buyer characteristics, such as dummies on “Male”, “Chinese”, and “Marriage”. For age, we use a dummy on “Old Age” that takes a value of 1, if a buyer is 60 year and older; and zero otherwise. The spatial fixed effect, which is represented by the 28 planning districts, and the transaction year fixed effects are included in the regression. Standard errors are reported in parenthesis. Regression results in Columns 1 and 2 are estimated using the full samples; whereas Column 3 is estimated using sub-samples periods 2005-2012. Column 4 and 5 are estimated using sub samples of new sale and resale.

*Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Table 7: Placebo Tests

Placebo cutoff year	2004	2005	2006	2007	2008	2009
Model	(1)	(2)	(3)	(4)	(5)	(6)
Agent × Placebo cutoff year	-0.0109 (0.0132)	-0.0263** (0.0131)	-0.0011 (0.0123)	-0.0007 (0.0100)	0.0140 (0.0134)	0.0114 -0.0093
Socioeconomic Variables	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,596	59,147	60,954	65,056	62,548	55,808
R-Squared	0.6835	0.7099	0.7405	0.7632	0.7616	0.7452

Note: Placebo cutoff year is used to falsify the policy shock in 2010 is specific to the CEA establishment in Singapore. The placebo cutoff year dummy divide the sample into the before (control) group and the after (treatment) group, and we use the same sample period of six years in each placebo tests. For instance, if the Placebo cutoff year is set at 2004, the two 3-year samples: 2001-2003 and 2004-2006 will be used as the “before” and “after” effects. The coefficients on housing attributes, buyers’ socioeconomic characteristics and transaction types as in Table 3 are not reported. All columns include year and region fixed effects.

*Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Table 8: Agents' Selection on Weak Sellers: Individual Sellers

Dependent variable	Individual seller	Investor seller	Institutional seller	Individual seller Exclude Institutional seller
Sample:	Resale Housing Samples			
Model	(1)	(2)	(3)	(4)
Agent	0.0215 (0.0137)	-0.0085 (0.0066)	-0.0130 (0.0127)	0.0097 (0.0103)
Size (square meters)	-0.0000 (0.0001)	-0.0002*** (0.0000)	0.0002*** (0.0001)	0.0003*** (0.0001)
Condominium	-0.0308*** (0.0084)	-0.0040 (0.0041)	0.0348*** (0.0078)	0.0005 (0.0063)
High Floor	0.0142** (0.0069)	-0.0034 (0.0034)	-0.0109* (0.0064)	0.0049 (0.0052)
Freehold	-0.0201** (0.0080)	-0.0011 (0.0039)	0.0213*** (0.0074)	0.0020 (0.0060)
Intercept	0.8255*** (0.0453)	0.0800*** (0.0220)	0.0944** (0.0422)	0.8791*** (0.0348)
Socioeconomic Variables	Yes	Yes	Yes	Yes
District Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	17,978	17,978	17,978	11,270
R-Squared	0.0761	0.0179	0.0995	0.0268

Notes: This table shows results of OLS regression analysis using only the resale samples. The dependent variables are represented by three binary variables that represent different sellers, such as individuals, investors and institutions. The binary variable has a value of 1, if a seller type is as defined in the top row of the table. “Agent” is dummy variable that has a value of 1, if a buyer is also an agent; and 0 otherwise. The control variables in the model include unit size (sqm), a dummy on condominium, a dummy on high floor that identifies unit located at level 9 and above, a dummy on new sale and a dummy on resale. The models also control for social-economic variations using the buyer characteristics, such as dummies on “Male”, “Chinese”, and “Marriage”. For age, we use a dummy on “Old Age” that takes a value of 1, if a buyer is 60 year and older; and zero otherwise. The spatial fixed effect, which is represented by the 28 planning districts, and the transaction year fixed effects are included in the regression. The first 3 Models (Columns 1, 2 and 3) are estimated using the full sample, and the last Model (Columns 4) is estimated using the sample that excludes institutional sellers. Standard errors are reported in parenthesis.

*Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Table 9: Agents' Selection on Weak Sellers: Sellers Involved Law Events

Dependent Variable:	Seller		Law events			
	involved in lawsuits	Bankruptcy	Car Accident	Sale of good	Credit Card	Tenancy
Model	(1)	(2)	(3)	(4)	(5)	(6)
Agent	0.0049 (0.0055)	0.0030 (0.0026)	0.0020 (0.0033)	-0.0007 (0.0009)	-0.0011 (0.0021)	0.0019* (0.0011)
Size (square meters)	-0.0000 (0.0000)	0.0000 (0.0000)	-0.0000** (0.0000)	0.0000 (0.0000)	0.0000* (0.0000)	-0.0000 (0.0000)
Condominium	-0.0115*** (0.0033)	-0.0028* (0.0015)	-0.0033* (0.0019)	-0.0008 (0.0005)	-0.0033*** (0.0012)	-0.0013* (0.0007)
High Floor	0.0006 (0.0027)	-0.0009 (0.0013)	0.0012 (0.0016)	0.0003 (0.0004)	0.0002 (0.0010)	-0.0002 (0.0006)
Freehold	-0.0019 (0.0031)	0.0003 (0.0015)	-0.0013 (0.0019)	0.0006 (0.0005)	-0.0016 (0.0012)	0.0001 (0.0006)
Intercept	0.0794*** (0.0191)	0.0111 (0.0090)	0.0584*** (0.0113)	-0.0012 (0.0031)	0.0084 (0.0072)	0.0028 (0.0039)
Socioeconomic Variables	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,737	40,737	40,737	40,737	40,737	40,737
R-Squared	0.0299	0.0226	0.0112	0.0029	0.0123	0.0034

Notes: The models are estimated using only the resale housing samples. The binary variable has a value of 1, if a seller type is as defined in the top row of the table. “Agent” is dummy variable that has a value of 1, if a buyer is also an agent; and 0 otherwise. The control variables in the model include unit size (sqm), a dummy on condominium, a dummy on high floor that identifies unit located at level 9 and above, a dummy on new sale and a dummy on resale. The models also control for social-economic variations using the buyer characteristics, such as dummies on “Male”, “Chinese”, and “Marriage”. For age, we use a dummy on “Old Age” that takes a value of 1, if a buyer is 60 year and older; and zero otherwise. The spatial fixed effect, which is represented by the 28 planning districts, and the transaction year fixed effects are included in the regression.

*Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Table 10: The Relationship between Housing price and Weak Sellers

Model	Seller involved in lawsuits		Individual seller		Individual seller (Exclude Institutional seller)	
	(1)	(2)	(3)	(4)	(5)	(6)
Weak seller	-0.0349*** (0.0046)	-0.0348*** (0.0045)	-0.0960*** (0.0040)	-0.0959*** (0.0040)	-0.0487*** (0.0081)	-0.0485*** (0.0081)
Agent		-0.0213*** (0.0051)		-0.0232*** (0.0073)		-0.0213*** (0.0080)
Size (square meters)	-0.0014*** (0.0000)	-0.0014*** (0.0000)	-0.0017*** (0.0000)	-0.0017*** (0.0000)	-0.0018*** (0.0000)	-0.0018*** (0.0000)
Condominium	0.1864*** (0.0030)	0.1862*** (0.0030)	0.1865*** (0.0045)	0.1862*** (0.0045)	0.1849*** (0.0049)	0.1846*** (0.0050)
High Floor	0.0408*** (0.0025)	0.0408*** (0.0025)	0.0367*** (0.0037)	0.0367*** (0.0037)	0.0340*** (0.0041)	0.0339*** (0.0041)
Freehold	0.1416*** (0.0029)	0.1414*** (0.0029)	0.1518*** (0.0043)	0.1516*** (0.0043)	0.1565*** (0.0047)	0.1563*** (0.0047)
Intercept	9.0464*** (0.0175)	9.0477*** (0.0175)	9.1517*** (0.0244)	9.1539*** (0.0244)	9.1820*** (0.0275)	9.1839*** (0.0275)
Socioeconomic Variables	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,737	40,737	17,978	17,978	13,847	13,847
R-Squared	0.7098	0.7100	0.7510	0.7511	0.7510	0.7747

Note: This table shows the relationship between housing price and weak sellers. The dependent variable is log-unit sale price (\$ per square meter) of houses. “Weak Seller” is a dummy variable that has a value of 1 if the seller is involved in lawsuits (column 1 and 2) or is an individual seller (column 3 to 6). “Agent” is dummy variable that has a value of 1, if a buyer is also an agent; and 0 otherwise. The control variables in the model include unit size (sqm), a dummy on condominium, a dummy on high floor that identifies unit located at level 9 and above, a dummy on new sale and a dummy on resale.

*Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Table 11: Bargaining Power of Real Estate Agents: Individual Sellers

	Resale Samples		Exclude
	(1)	(2)	Institutional seller (3)
Agent	-0.0209** (0.0083)	-0.0209** (0.0084)	-0.0220*** (0.0082)
Institutional seller	0.1055*** (0.0083)	0.1056*** (0.0044)	
Investor seller	0.0554*** (0.0084)	0.0562*** (0.0085)	0.0477*** (0.0084)
Agent×Institutional seller	-0.0160 (0.0180)	-0.0160 (0.0181)	
Agent×Investor seller	0.0099 (0.0357)	0.0173 (0.0361)	0.0130 (0.0353)
Size (square meters)	-0.0018*** (0.0000)	-0.0017*** (0.0000)	-0.0018*** (0.0000)
Condominium	0.0371*** (0.0044)	0.1857*** (0.0045)	0.1846*** (0.0049)
High Floor	0.0371*** (0.0037)	0.0367*** (0.0037)	0.0339*** (0.0041)
Freehold	0.1515*** (0.0042)	0.1513*** (0.0043)	0.1563*** (0.0047)
Intercept	9.0762*** (0.0231)	9.0602*** (0.0241)	9.1355*** (0.0265)
Socioeconomic Variables	No	Yes	Yes
District Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Observations	18,148	18,148	13,847
R-Squared	0.7516	0.7515	0.7747

Notes: This table shows results of OLS regression analysis using the resale samples. The dependent variable is the log-unit price (\$per square meter) of houses. “Agent” is dummy variable that has a value of 1, if a buyer is also an agent; and 0 otherwise. The control variables in the model include unit size (sqm), a dummy on condominium, a dummy on high floor that identifies unit located at level 9 and above, a dummy on new sale and a dummy on resale. The models also control for social-economic variations using the buyer characteristics, such as dummies on “Male”, “Chinese”, and “Marriage”. For age, we use a dummy on “Old Age” that takes a value of 1, if a buyer is 60 year and older; and zero otherwise. The spatial fixed effect, which is represented by the 28 planning districts, and the transaction year fixed effects are included in the regression. Standard errors are reported in parenthesis. Regression results in Columns 1 and 2 are estimated using the full sample, whereas, column 3 is estimated using samples that exclude institutional sellers.

*Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Table 12: Bargaining Power of Real Estate Agents: Sellers Involved Law Events

Sample:	Resale Sample		Truncated Sample#
	(1)	(2)	(3)
Agent	-0.0205*** (0.0052)	-0.0205*** (0.0052)	-0.0204*** (0.0052)
Lawsuits	-0.0340*** (0.0047)		
Agent×Lawsuits	-0.0134 (0.0187)		
Before Lawsuits		-0.0327*** (0.0105)	-0.0308*** (0.0110)
After Lawsuits		-0.0414*** (0.0101)	-0.0400*** (0.0105)
Agent×Before Lawsuits		0.0660 (0.0402)	0.0724* (0.0420)
Agent×After Lawsuits		-0.0856** (0.0371)	-0.0805** (0.0385)
Size (square meters)	-0.0014*** (0.0000)	-0.0014*** (0.0000)	-0.0014*** (0.0000)
Condominium	0.1862*** (0.0030)	0.1863*** (0.0030)	0.1858*** (0.0030)
High Floor	0.0408*** (0.0025)	0.0408*** (0.0025)	0.0412*** (0.0025)
Freehold	0.1414*** (0.0029)	0.1414*** (0.0029)	0.1419*** (0.0029)
Intercept	9.0477*** (0.0175)	9.0477*** (0.0175)	9.0430*** (0.0177)
Socioeconomic Variables	Yes	Yes	Yes
Spatial Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Observations	40,737	40,737	39,933
R-Squared	0.7100	0.7099	0.7090

Notes: The models are estimated using only the resale housing samples. (# Transactions for sellers involved in lawsuits are excluded if a transaction is done more than 3 years before or after the lawsuits date). The dependent variable is the log-unit price (\$per square meter) of houses. “Agent” is dummy variable that has a value of 1, if a buyer is also an agent; and 0 otherwise. “Before” and “After” are time dummies that represent transactions that occur before or after the law events convicted by sellers. The control variables in the model include unit size (sqm), a dummy on condominium, a dummy on high floor that identifies unit located at level 9 and above, a dummy on new sale and a dummy on resale. The models also control for social-economic variations using the buyer characteristics, such as dummies on “Male”, “Chinese”, and “Marriage”. For age, we use a dummy on “Old Age” that takes a value of 1, if a buyer is 60 year and older; and zero otherwise. The spatial fixed effect, which is represented by the 28 planning districts, and the transaction year fixed effects are included in the regression. Standard errors are reported in parenthesis.

*Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Table 13: Agent Buyers and Sellers with Lawsuits: Resale Market

lawsuits type (φ_i)	Bankruptcy	Car Accident	Sale of good	Credit Card	Tenancy
	(1)	(2)	(3)	(4)	(5)
Agent	-0.0209*** (0.0051)	-0.0213*** (0.0051)	-0.0216*** (0.0051)	-0.0210*** (0.0051)	-0.0214*** (0.0051)
Before Lawsuits φ_i	-0.0661*** (0.0141)	-0.0057 (0.0170)	0.0842 (0.0607)	-0.0372 (0.0264)	0.0534 (0.0461)
After Lawsuits φ_i	-0.0363** (0.0166)	-0.0004 (0.0146)	-0.0813 (0.0543)	-0.0996*** (0.0173)	-0.1279*** (0.0370)
Agent× (Before Lawsuits φ_i)	0.1315** (0.0597)	0.0245 (0.0595)	0.0405 (0.1779)	0.0463 (0.1325)	-0.0539 (0.1659)
Agent× (After Lawsuits φ_i)	-0.1608*** (0.0578)	-0.0403 (0.0537)		-0.1060 (0.0742)	0.0443 (0.1290)
Size (square meters)	-0.0014*** (0.0000)	-0.0014*** (0.0000)	-0.0014*** (0.0000)	-0.0014*** (0.0000)	-0.0014*** (0.0000)
Condominium	0.1865*** (0.0030)	0.1866*** (0.0030)	0.1866*** (0.0030)	0.1864*** (0.0030)	0.1865*** (0.0030)
High Floor	0.0408*** (0.0025)	0.0408*** (0.0025)	0.0408*** (0.0025)	0.0408*** (0.0025)	0.0407*** (0.0025)
Freehold	0.1414*** (0.0029)	0.1415*** (0.0029)	0.1415*** (0.0029)	0.1413*** (0.0029)	0.1415*** (0.0029)
Intercept	9.0460*** (0.0175)	9.0451*** (0.0176)	9.0449*** (0.0175)	9.0460*** (0.0175)	9.0450*** (0.0175)
Socioeconomic Variables	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	40,737	40,737	40,737	40,737	40,737
R-Squared	0.7099	0.7095	0.7096	0.7100	0.7096

Notes: This table shows the OLS regressions with the log-unit sale price (\$ per square meter) of houses as the dependent variable. “Agent” is dummy variable that has a value of 1, if a buyer is also an agent; and 0 otherwise. “Before” and “After” are time dummies that represent transactions that occur before or after the law events convicted by sellers. We condition the timing of transactions on different law events, [φ_i = car accident, sale of good, credit card, tenancy and bankruptcy]. The control variables in the model include unit size (sqm), a dummy on condominium, a dummy on high floor that identifies unit located at level 9 and above, a dummy on new sale and a dummy on resale. Social-economic variations are controlled in the model using the buyer characteristics, such as dummies on “Male”, “Chinese”, and “Marriage”. For age, we use a dummy on “Old Age” that takes a value of 1, if a buyer is 60 year and older; and zero otherwise. The district fixed effect, which is represented by the 28 planning districts, and the transaction year fixed effects are included in the regression. Standard errors are reported in parenthesis.

*Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Table 14: Agent Discounts for Investor Buyers

	Resale Samples		Newsale Samples	
	(1)	(2)	(3)	(4)
Agent	-0.0212*** (0.0057)	-0.0205*** (0.0057)	-0.0178*** (0.0042)	-0.0164*** (0.0042)
Investor buyer	0.0011 (0.0031)	0.0013 (0.0032)	-0.0123*** (0.0019)	-0.0128*** (0.0019)
Agent × Investor buyer	-0.0037 (0.0122)	-0.0048 (0.0123)	0.0070 (0.0082)	0.0076 (0.0082)
Size (square meters)	-0.0014*** (0.0000)	-0.0014*** (0.0000)	-0.0009*** (0.0000)	-0.0009*** (0.0000)
Condominium	0.1862*** (0.0030)	0.1866*** (0.0030)	0.0344*** (0.0022)	0.0348*** (0.0022)
High Floor	0.0410*** (0.0025)	0.0407*** (0.0025)	0.0393*** (0.0017)	0.0396*** (0.0017)
Freehold	0.1416*** (0.0029)	0.1415*** (0.0029)	0.1223*** (0.0022)	0.1223*** (0.0022)
Intercept	9.0513*** (0.0169)	9.0444*** (0.0176)	9.4002*** (0.0203)	9.4031*** (0.0208)
Socioeconomic Variables	No	Yes	No	Yes
District Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	41,141	40,737	58,687	58,071
R-Squared	0.7097	0.7095	0.8025	0.8028

Note: This table shows results of OLS regression analysis about agent discounts for investor buyers. The dependent variable is log-unit sale price (\$ per square meter) of houses. “Agent” is dummy variable that has a value of 1, if a buyer is also an agent; and 0 otherwise. The control variables in the model include unit size (sqm), a dummy on condominium, a dummy on high floor that identifies unit located at level 9 and above, a dummy on new sale and a dummy on resale. Standard errors are reported in parenthesis. Regression results in Columns 1 and 2 are estimated using resale samples; whereas Columns 3 and 4 are estimated using new sale samples.

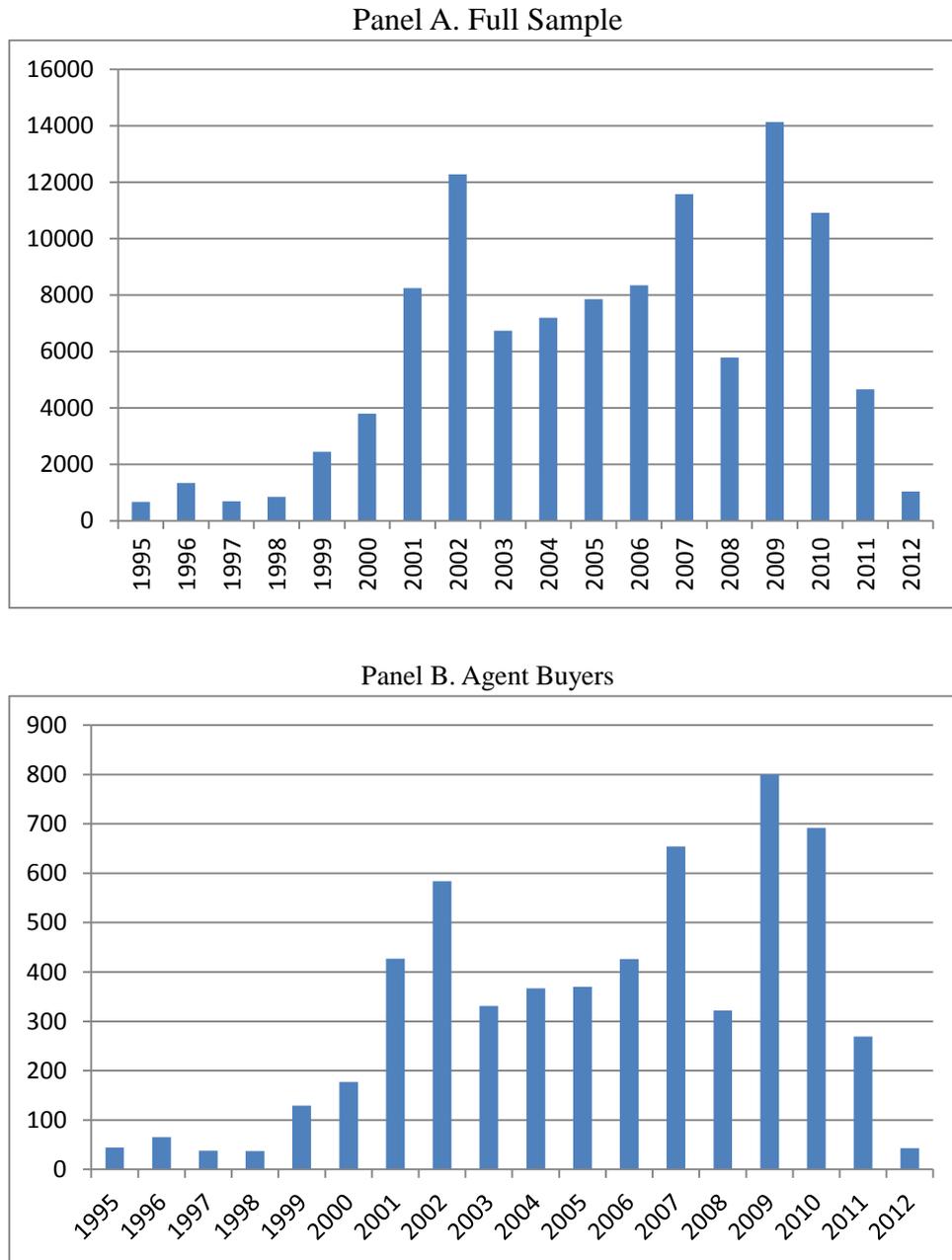
*Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Table 15: Agent Discounts and Transaction Time

	All Sample		
	(1)	(2)	(3)
Agent	-0.0102 (0.0107)	-0.0142*** (0.0048)	-0.0266* (0.0148)
Agent*month1	-0.0120 (0.0153)		
Agent*month2	-0.0187 (0.0151)		
Agent*month3	-0.0192 (0.0148)		
Agent*month4	-0.0044 (0.0142)		
Agent*month5	-0.0137 (0.0144)		
Agent*month6	0.0005 (0.0144)		
Agent*month7	-0.0074 (0.0138)		
Agent*month8	-0.0153 (0.0140)		
Agent*month9	-0.0089 (0.0149)		
Agent*month10	-0.0055 (0.0155)		
Agent*month11	0.0041 (0.0158)		
Agent*3 month SIBOR		-0.0016 (0.0014)	
Agent*House Price Index			0.0001 (0.0001)
Intercept	9.3362*** (0.0124)	9.2892*** (0.0122)	7.7803*** (0.0223)
Housing Characteristics	Yes	Yes	Yes
Socioeconomic Variables	Yes	Yes	Yes
District Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Observations	107,399	107,399	107,399
R-Squared	0.7716	0.7678	0.7806

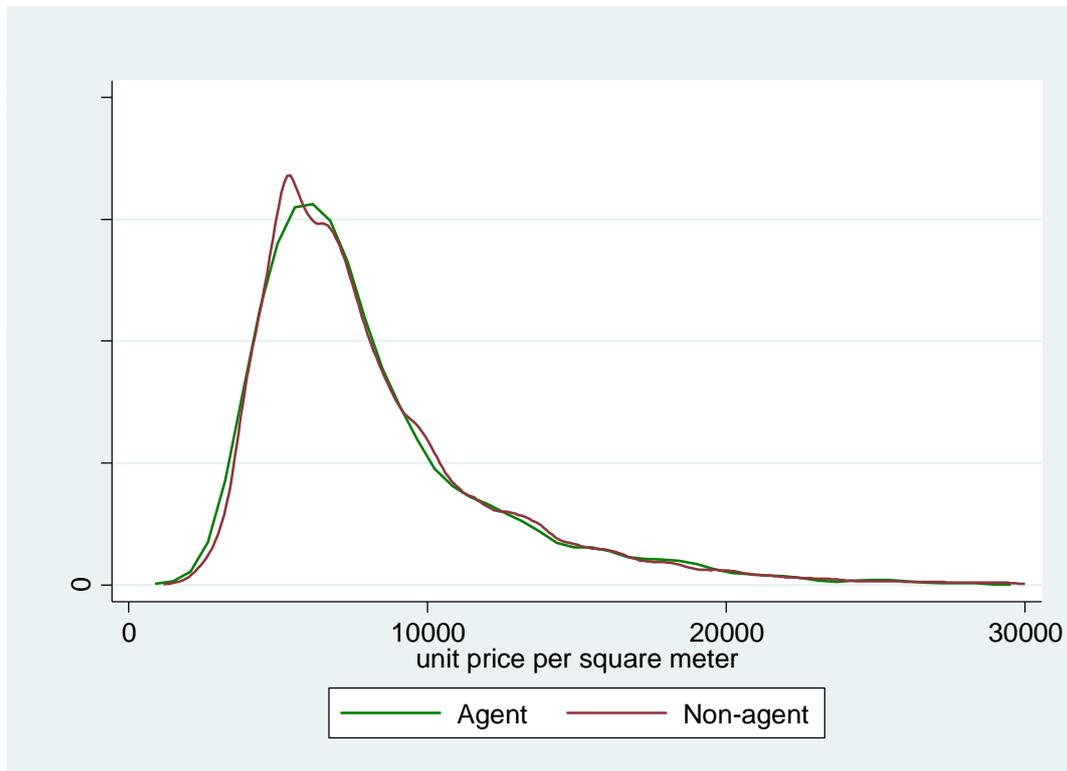
Note: This table shows results of OLS regression analysis about agent discounts and transaction time. The dependent variable is log-unit sale price (\$ per square meter) of houses. 3 month Singapore Interbank Overnight Rate (SIBOR) is usually the index rate for home mortgage in Singapore. We use price index of non-landed properties from Urban Redevelopment Authority (URA) as our housing price index. *Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Figure 1: Transaction Frequency over Years



Note: The figures show the transaction frequencies by year for the period from 1995 to 2012. Panel (A) shows the frequency distributions for the full sample and Panel (B) shows the distributions for only the agent-buyer sample.

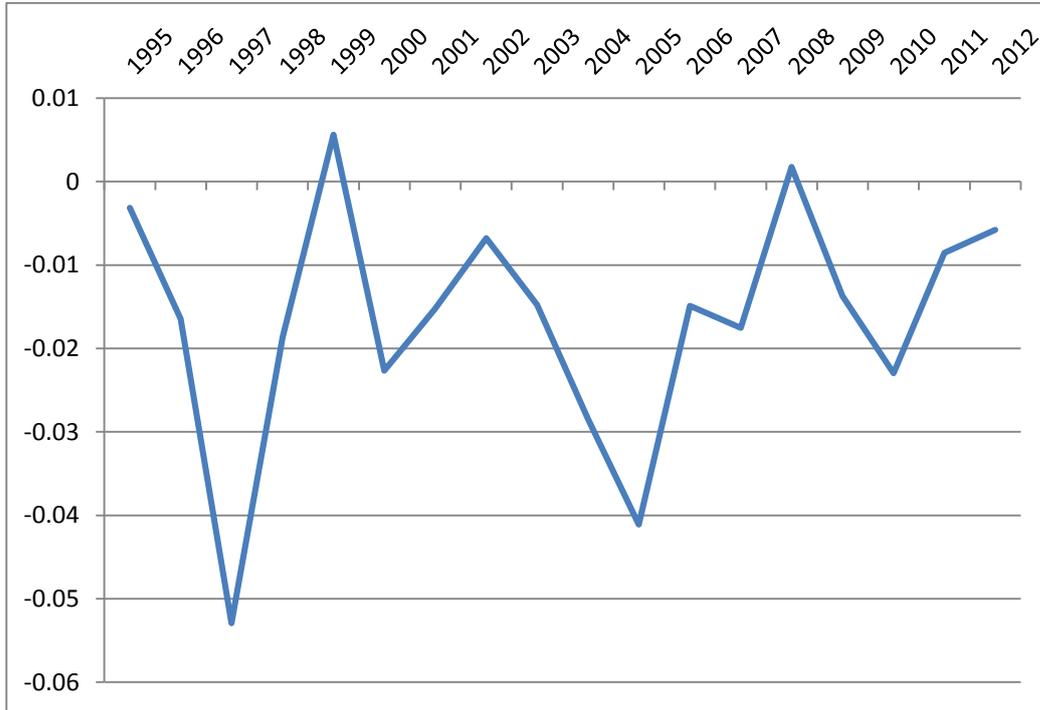
Figure 2: Kernel Density Plot of Unit Price Per Square Meter



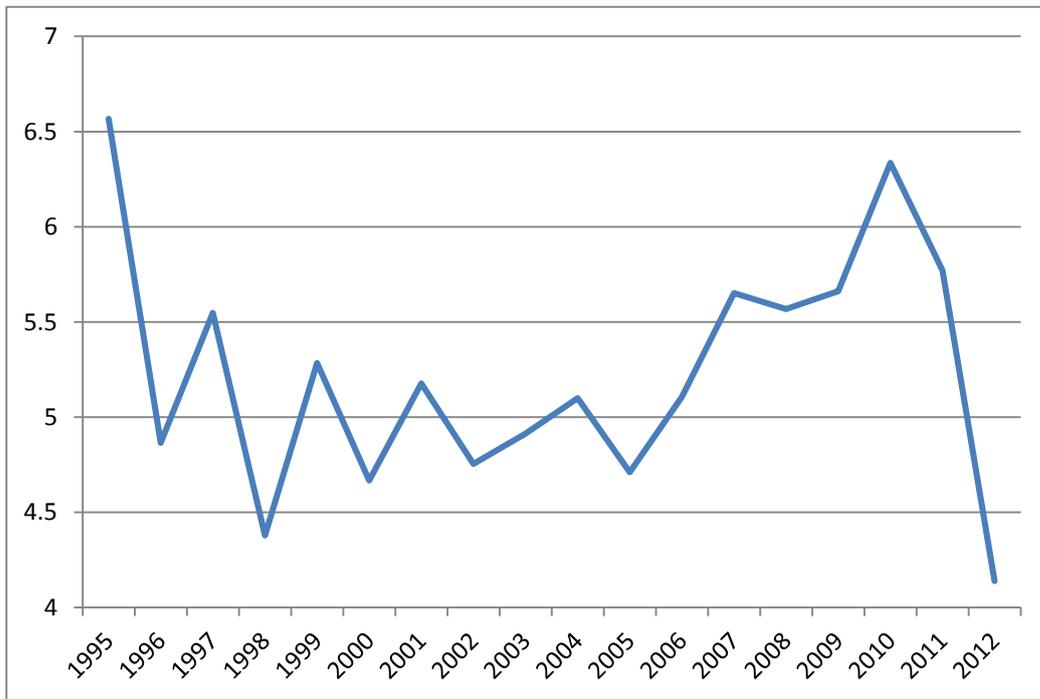
Note: This figure shows the kernel density plots of unit price per square meter for agent and non-agent. The Y-axis indicates the probability of density, and the X-axis indicates the value distribution of the unit price per square meter.

Figure 3: Agent's Transactions over Years

Panel A. Agent's Discount on Unit Price per Square Meter over Years



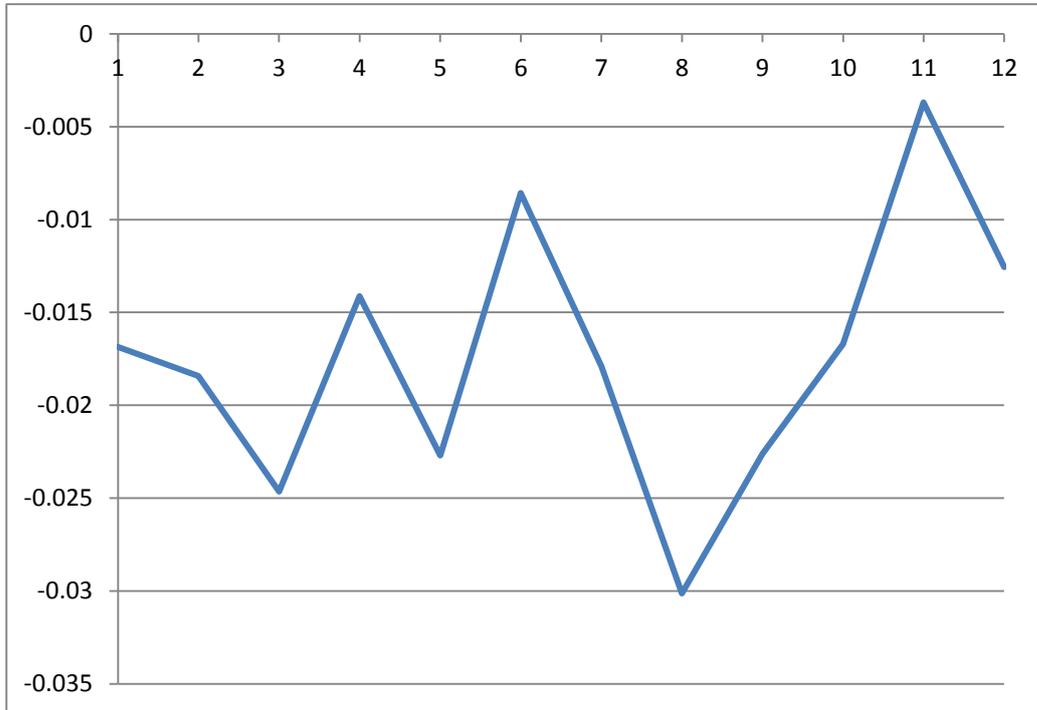
Panel B. Proportion of Agent's Transaction over Time



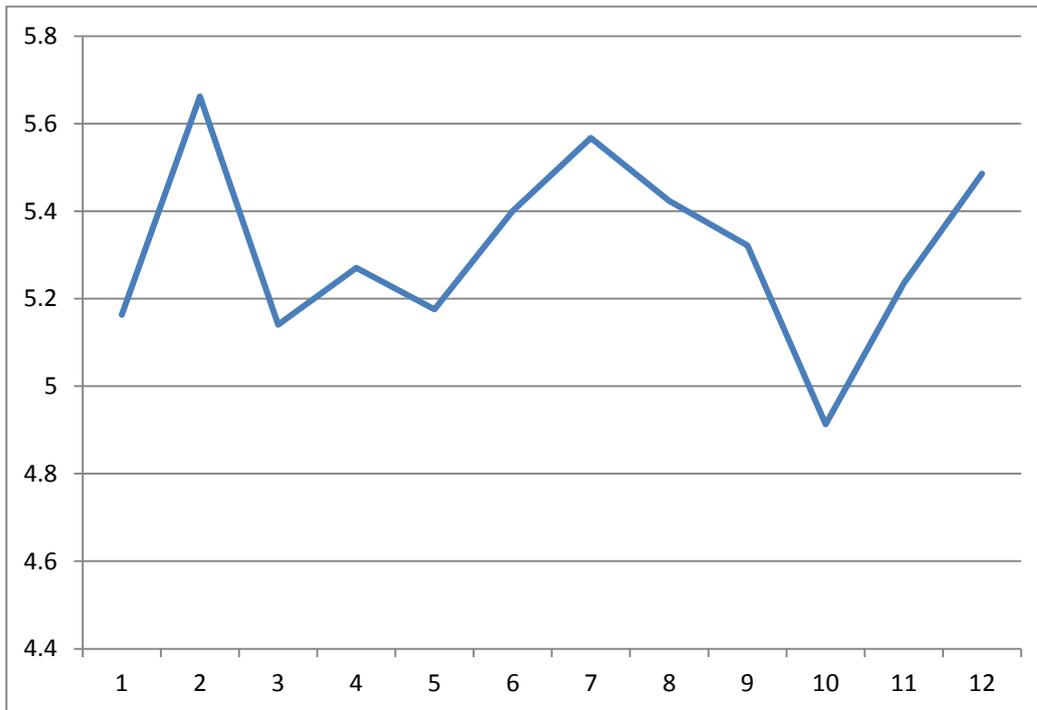
Note: This figure shows the agent discount over years and the proportion of agent transactions over years.

Figure 4: Agent's Transactions by Month

Panel A. Agent's Discount on Unit Price per Square Meter over Month



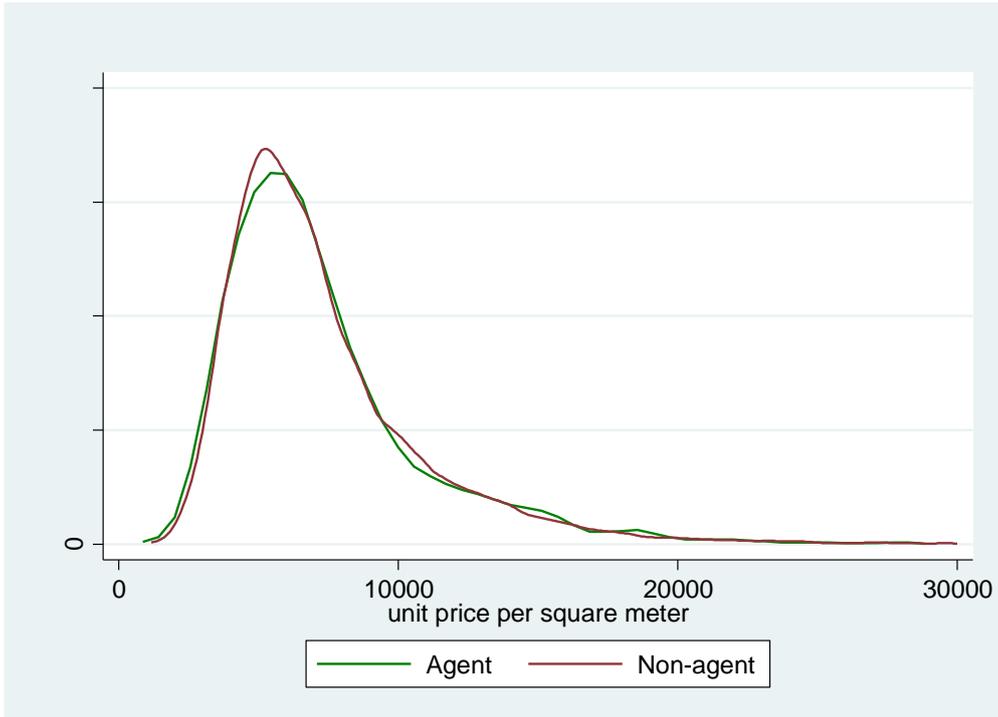
Panel B. Proportion of Agent's Transaction over Months



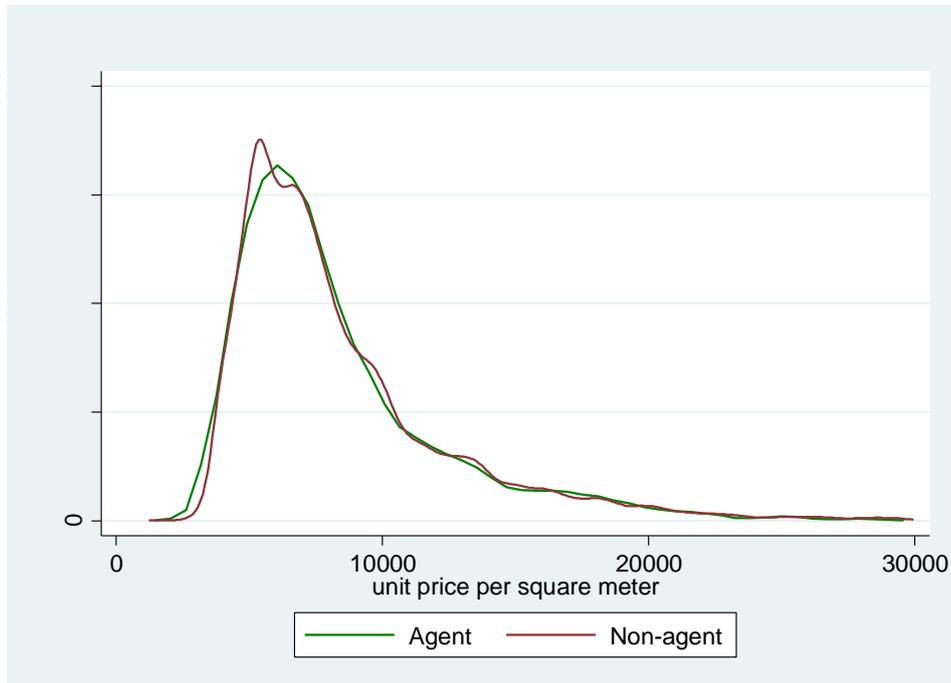
Note: This figure shows the agent discount over months and the proportion of agent transactions over months.

Figure 5: Kernel Density Plot of Unit Price Per Square Meter

Panel A. Resale Market

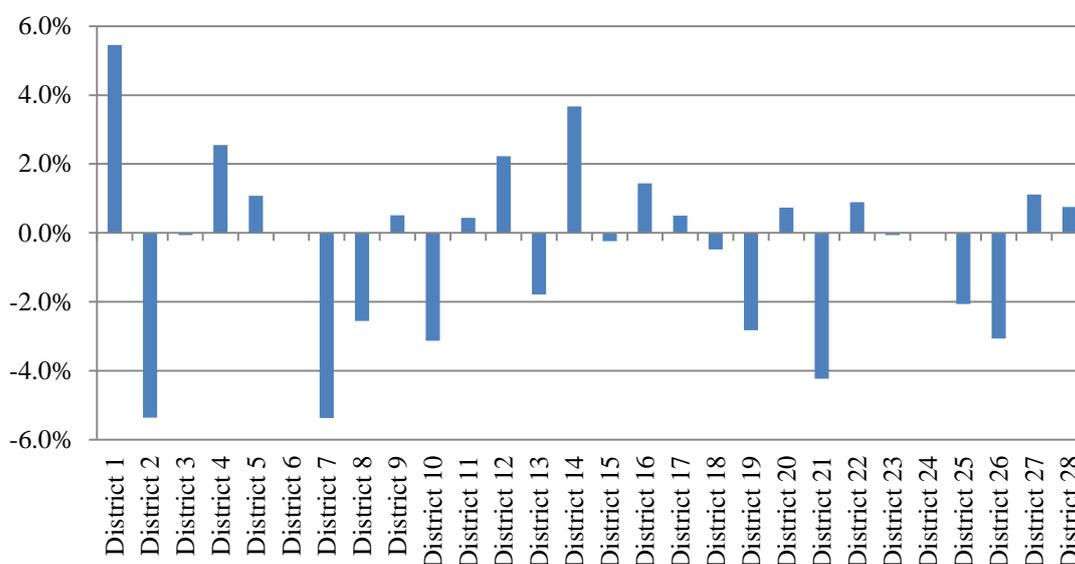


Panel B. New Sale Market



Note: This figure shows the kernel density plots of unit price per square meter for agent and non-agent in resale market and newsale market. The Y-axis indicates the probability of density, and the X-axis indicates the value distribution of the unit price per square meter.

Figure 6: Price Differences between Agent and Non-Agent Housing Transactions by District



Legend on Districts and Areas Covered:

District	Name of Areas Covered	District	Name of Areas Covered
1	Raffles Place, Marina, Cecil	15	Joo Chiat, Marina Parade, Katong
2	Tanjong Pagar, Chinatown	16	Bedok, Upper East Coast, Siglap
3	Tiong Bahru, Alexandra, Queenstown	17	Changi, Flora, Loyang
4	Mount Faber, Telok Blangah, Harbourfront	18	Tampines, Pasir Ris
5	Buona Vista, Pasir Panjang, Clementi	19	Punggol, Sengkang, Serangoon Gardens
6	Clarke Quay, City Hall	20	Ang Mo Kio, Bishan, Thomson
7	Bugis, Beach Road, Golden Mile	21	Upper Bukit Timah, Ulu Pandan, Clementi Park
8	Little India, Farrer Park	22	Boon Lay, Jurong, Tuas
9	Orchard Road, River Valley	23	Choa Chu Kang, Dairy Farm, Hillview, Bukit Panjang, Bukit Batok
10	Bukit Timah, Holland, Balmoral	24	Kranji, Lim Chu Kang, Tengah
11	Novena, Newton, Thomson	25	Woodlands, Admiralty
12	Toa Payoh, Serangoon, Balestier	26	Upper Thomson, Mandai
13	Macpherson, Braddell	27	Sembawang, Yishun, Admiralty
14	Geylang, Paya Lebar, Sims	28	Yio Chu Kang, Seletar

Note: This figure shows % differences in average unit price (S\$psm) between houses bought by agents and non-agents, sorted by district. A negative number indicates a discount in the transaction prices, which mean that an agent buys a comparable house for his/her own use at lower prices than other a non-agent buyer; whereas, a positive number indicates that an agent pay a higher price for a comparable house than non-agent buyer. We compute average price differences sorted by district. There are 28 planning districts in Singapore, and detailed descriptions of areas bounded under each district are shown in the appended table.

Figure 7: Adjusted Housing Price for Agent and Non-Agent Buyers



Note: This figure shows the Adjusted Housing Price for Agent and Non-Agent Buyers over time. The vertical axis is the adjusted housing price normalized by Singapore's housing price index. The horizontal axis is the year of housing transaction.