

# In-House Transactions in the Real Estate Brokerage Industry: Matching Outcome or Strategic Promotion?\*

Lu Han  
Rotman School of Management  
University of Toronto  
lu.han@rotman.utoronto.ca

Seung-Hyun Hong  
Department of Economics  
University of Illinois  
hyunhong@illinois.edu

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## Abstract

Over 20% of residential real estate transactions are in-house transactions, for which buyers and sellers are represented by the same brokerage. To investigate the underlying mechanisms that generate these in-house transactions, we first construct a search model that predicts two types of in-house transactions with different implications for market efficiency. The first is strategic promotion in that a cooperating agent may influence buyers' choices by directing their interest to houses listed by his brokerage firm. The second is a matching outcome in that brokerage firms may specialize in certain segments of housing markets, thus attracting interest from buyers and sellers with similar tastes. Using home transaction data from a large metropolitan area, we find that agents are more likely to promote houses listed by their own firms when they receive promotion bonus from the firms and when buyers have higher search cost. The results are robust even after we control for efficient matching due to information advantages and transaction efficiencies. We then develop a structural model of in-house transactions to quantify the extent of strategic promotion and further evaluate welfare consequences of a legislation that requires agents to disclose dual agency relationship to their clients. We find that while about 70% of in-house transactions can be explained by efficient matching, the remaining are caused by agents' strategic promotion. In addition, the legislation has weakened the impact of agents' strategic promotion on the home allocation process, which accounts for 41% of the decrease in in-house transactions before and after the regulatory change.

*Keywords:* real estate brokerage, in-house transaction, strategic promotion, matching

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# 1 Introduction

Over 80% home buyers and sellers carry out their home transactions with the assistance of a licensed real estate agent. Yet concerns persist that the misalignment between the goals of agents and those of their clients can cause a loss in consumers' benefit. For example, recent literature has shown that the current commission structure lead real estate agents to leave their own homes on the market longer and sell at a higher price on average, compared to homes they sell for their clients (Levitt and Syverson 2008; Rutherford, Springer, and Yavas 2005).

A phenomenon that is equally important for understanding the incentive misalignment in the real estate brokerage industry but has received less attention is in-house transactions, that is, transactions for which buyers and sellers are represented by the same brokerage firm. Since a brokerage firm engaged in in-house transactions profits from both sides of a transaction, it often pays a higher commission to reward agents that promote such sales (Gardiner, Heisler, Kallberg, and Liu, 2007).<sup>1</sup> However, this type of promotion may lower the quality of the match for home buyers and sellers, creating a distortion in the home transaction process to benefit agents.

In this paper, we examine the causes and implications of in-house transactions in the residential real estate brokerage industry, using home transaction data between 2001-2009 from a large North American metropolitan area. In our sample, about 20% of transactions occur within the same brokerage firm; about 30% of transactions occur within the same franchise.<sup>2</sup> One might wonder whether these in-house transactions can simply be a result of independent hiring decisions made separately by buyers and sellers. In that case, conditional on a given buyer working with brokerage  $j$ , the probability that the buyer purchases a house listed by the same brokerage should be equal

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<sup>1</sup>Commissions are typically evenly split between the listing and cooperating brokerage offices. Each office then pays its participating agent a percentage of the total. Based on evidence from Gardiner, et. al. (2007) and our own observations from the sample data, brokerage firms that promote in-house sales have a higher likelihood of capturing both sides of commissions, which creates a natural incentives for firms to promote in-house sales.

<sup>2</sup>In-house transactions refer to brokerage-level in-house transactions for which the listing agent (seller's agent) and the cooperating agent (buyer's agent) work for the same brokerage. Because many brokerages are franchisees of the same franchise, we also use franchise-level in-house transactions to indicate transactions for which the cooperating brokerage and the listing brokerage belong to the same franchise.

to the market share of listing brokerage  $j$ . In other words,

$$\Pr(\text{listing} = j | \text{cooperating} = j) = \Pr(\text{listing} = j). \quad (1)$$

However, as shown in Figure 1, brokerage-level fractions of in-house transactions at any given district of the sample city are much higher than the dashed line which depicts the fractions predicted from (1). This suggests that a significant fraction of in-house transactions cannot be explained by independent interactions among brokerage firms.

Economists have long speculated about the efficiency loss associated with in-house transactions, but few studies have been able to explain the underlying mechanisms or to quantify the magnitude of the efficiency loss. Our study is among the first to get inside the black box of in-house transactions and to shed light on the determinants and welfare loss associated with in-house transactions. To do so, we examine the extent to which these transactions represent brokerage firms' own interest rather than the best interest of home buyers and sellers, both theoretically and empirically.

At the theory front, we construct an agent-intermediated search model that has three key ingredients. The first ingredient is search cost: each buyer has an idiosyncratic valuation for each house which can be learned through costly search. The second ingredient is the information advantage enjoyed by real estate agents relative to buyers with high search cost. The third ingredient is a promotion bonus that agents receive from their affiliated firms for selling listings originated from the same firm.

In an environment with these three ingredients, two types of in-house transactions naturally arise: *matching-based* and *strategically-promoted* in-house transactions. In the first case, buyers and sellers may choose to work with the same brokerage because they share the same preference for the type of expertise that the brokerage specializes in. The agents affiliated with this brokerage are believed to possess superior information about both sides of a certain market segment, permitting them to better match buyers with sellers. In this case, having the cooperating and listing agents from the same brokerage creates transaction efficiencies, leading to an efficient match between consumers' preference and the type of agents best able to serve them.

However, in-house transactions can also occur for incentive rather than efficiency reasons. When

agents are financially rewarded for selling listings originated from the same brokerage, the information advantage that agents possess relative to their clients compounds incentive conflicts, making it possible for cooperating agents to influence buyers' choice by directing their interest to houses listed with the same brokerage. This mechanism is particularly effective when cooperating agents receive less compensation from listing agents and when buyers have high search costs. This type of transactions clearly creates a distortion to the matching process that benefits agents themselves rather than buyers and sellers.

To test these implications, we utilize a rich dataset that covers one third of properties transacted in the Multiple Listing Service (MLS) in a large North American metropolitan area from January 2001 to December 2009, with over 200,000 transactions and more than 1,000 brokerage firms. The dataset has three appealing features. First, it contains detailed information about house characteristics, neighborhood information, listing and transaction price, as well as real estate brokerage firms on both sides of a transaction. Second, it includes properties that have been transacted multiple times, which allows us to control for unobserved house characteristics. Third, the sample period covers a natural experimental opportunity permitted by a new legislation (Real Estate and Business Brokerages Act – referred to as “REBBA” hereafter) that requires agents engaged in in-house sales to inform their clients about the dual agency relationship in writing. This allows us to examine the strength of strategic promotions in a setting where market participants are less aware of the the dual agency relationship and then, after the legislation, it is fully disclosed.

Exploiting these unique data, we first estimate a reduced-form model of in-house transactions. Using various brokerage-specific and property-specific features that are tied to the model's predictions, we seek to distinguish between two forms of in-house transactions: strategically-promoted and matching-based. The former depends on buyers' search cost and agents' incentive and ability to promote their own firms' listings; while the latter depends on whether certain characteristics of houses fall within the “territory” of firms' specialization. To further identify the effect of strategic promotion, we exploit the REBBA regulation, which presumably constrains agents' ability to promote internal listings, while leaving other types of in-house transactions unaffected.

We find that agents' strategic incentives play an important role in explaining in-house transactions. First, the lower commission rates that cooperating agents received from listing agents are associated with a stronger presence of in-house transactions. This is consistent with the theory as lower commission rates make cooperating agents more likely to respond to the financial incentives offered by brokerage firms and hence more likely to promote internal listings. Second, we find that such commission effect is economically and statistically significant only for buyers with higher search costs – the latter being proxied by the difficulty of accessing public transportation systems. Buyers with lower search costs have more complete information about housing markets, and hence are less likely to be influenced by agents. Third, we find that the presence of strategic in-house transactions is substantially weakened – yet still sizeable – after the introduction of REBBA.

Together, these findings are highly in line with the predictions from the theory. These results are robust to a rich set of controls, including observed and unobserved housing characteristics, property assessment value, and the listing price. We also consider a variety of tests examining whether the estimated strategic in-house transactions can be explained by efficient matching based on home buyers' and seller' own interest. The tests confirm that the patterns we see in the data are unlikely explained by brokerage specialization either in geographical areas or in price segments.

In light of the findings for the presence and determinants of strategic promotions, we then proceed to estimate a structural model of in-house transactions to evaluate the economic impact of strategic promotions as well as understanding the welfare consequence of the REBBA. Our basic identification strategy relies on the following optimal decision rule: the observed in-house choice is an indicator of a buyer's comparison between her utility from shopping internal listings and from shopping external listings. Hence, by observing whether a transaction occurs within the same brokerage as well as by estimating the idiosyncratic matching value that a buyer obtains from internal and external listings, we can in principle recover the net cost associated with buying a house listed by other brokerages versus buying a house from internal listings. To this end, we first use a nonparametric hedonic approach developed by Bajari and Benkard (2005) to recover buyer-specific preference for house characteristics, and then exploit econometric matching techniques

(e.g., Heckman, et al. 1997, 1998) to further recover the idiosyncratic matching value that a buyer obtains from internal listings as well as from external listings. This allows us to estimate the extra cost that agents impose on buyers for purchasing houses listed by other brokerages. Such cost should be higher when agents are rewarded for promoting internal listings, and the effect should be weaker when agents' promotion ability is constrained. To quantify the part of cost that occurred for incentive reasons and to evaluate the associated welfare loss for buyers, we exploit variations generated by commission structure combined with the REBBA policy, both of which are motivated by the theory.

We find that while about 70% of in-house transactions are caused by a mixture of information advantages and transaction efficiencies associated with brokerage specialization, the remaining are explained by agents' strategic promotion. In the latter case, a buyer whose interest is best matched by a house listed by other brokerages ends up purchasing a house from internal listings as a result of her agents' strategic promotion. We also find that, before the implementation of the REBBA, the agent's promotion caused the buyer a utility loss of 1.68% (relative to the potential utility she could have obtained in the absence of promotion) – a number that is almost comparable to the commission income that an agent earns from completing a transaction when translated into the monetary value. Such loss was reduced to 0.35% after the implementation of the REBBA, suggesting that the legislation does have some desired effects by helping homebuyers make more informed choices and by constraining agents' ability to strategically promote.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 provides background information about the residential real estate brokerage industry, and presents a simple agent-intermediated search model that generates key predictions. Section 4 describes our data and Section 5 provides reduced form evidence that confirms the predictions from the theory. Section 6 further develops a structural model of in-house transactions that allows us to quantify the extent of strategic promotion and its associated welfare loss. Section 7 presents the results from our structural estimation. Section 8 concludes the paper.

## 2 Related Literature

This paper contributes to an important and substantial literature on the distortion of agents' incentives (e.g., Gruber and Owings 1996; Mehran and Stulz 1997; Hubbard 1998; Garmaise and Moskowitz 2004). More specifically, it complements recent literature that examines competition and efficiency in the real estate brokerage industry (e.g., Yavas 1992; Hsieh and Moretti 2003; Merlo and Ortalo-Magne 2004; Han and Hong 2011; Jia Barwick and Pathak 2011). Although there is an increasing body of work devoted to studying the consequences of incentive misalignment on house price and time on the market (Rutherford, Springer, and Yavas 2005; Levitt and Syverson 2008; Hendel, Nevo, Ortalo-Magne 2009), little work has empirically examined the impact of incentive misalignment for home buyers. This is probably due, in large part, to the difficulty of determining the quality of a match between a buyer and a house. In this paper, we take a structural approach to recover the idiosyncratic match value for home buyers, which permits us to evaluate the economic harm that the incentive misalignment brings to homebuyers. Such evaluation contributes to a better understanding of the efficiency of in this important industry. In a world where agents' interests are fully aligned with home buyers' interests, there should be no efficiency loss associated with in-house transactions since all transactions represent the best matching outcome for buyers. In contrast, if agents strategically interfere with the allocation of houses to individuals, consumers' benefit would be inevitably sacrificed, and a lower quality match would be resulted. This paper shows that the latter is indeed the case.

Despite the sheer magnitude of in-house transactions, there has been surprisingly little work that examines dual agency in real estate markets. Gardiner, Heisler, Kallberg, and Liu (2007) are among the first to study the impact of dual agency in residential housing markets. They exploit a natural experimental opportunity permitted by a law change in Hawaii in 1984 requiring full disclosure of dual agency. Using repeated sales properties, Evans and Kolbe (2005) study the effect of dual agency on home price appreciation. In addition, Kadiyali, Prince, and Simon (2012) examine the impact of dual agency on time on the market, sales and listing price. This paper differs from the previous work in three ways. First, it provides an economic model that rationalizes

the mechanism that generates in-house sales. Second, instead of focusing on the price and time on the market, this paper examines how dual agency affects home allocation process and quality of the match. The former are measures of transaction outcome that matter more for sellers; while the latter are key measures of transaction outcome for home buyers. Finally, using a structural approach, this paper is able to quantify the extent of strategic promotion versus efficient matching in explaining in-house transactions and further evaluate the welfare consequence of a legislation that requires agents to disclose their agency relationship.

### **3 In-House Transactions in the Residential Real Estate Brokerage**

#### **3.1 Residential Real Estate Brokerage Industry**

Real estate brokers and agents are licensed professionals whose main job is to match a home seller with a home buyer. Together, they provide a bundle of services to buyers and sellers. An agent working with buyers is often referred to as the “cooperating agent” or “selling agent.” Cooperating agents typically attempt to find houses that match buyers’ taste, show buyers prospective homes, advise them in making offers, and provide assistance in negotiation process. Under the current system, buyers do not pay cooperating agents directly. However, they do share some of the cost of their agents’ services, since the commission fees would be capitalized into the price that they pay for the house.

An agent working with sellers is often referred to as the “listing agent.” The listing agent helps sellers list the house on the MLS, assist sellers in staging and marketing the house, advise sellers on the listing price, help sellers evaluate offers and formulate counteroffers, help negotiate directly with the buyer or the buyer’s agent, and provide assistance in closing a transaction. In return, the seller pays the listing agent a predetermined fee, typically 5 – 6% of the sale price, which is then split between the listing and cooperating agents who facilitate the deal.

A brokerage firm, which includes one or more brokers, agents and support staffs, can either operate independently or affiliate with a local, regional or national real estate franchised company. Brokerage firms provide agents with branding, advertising, and other services that help the agents

complete transactions. In return for the brand value and for the supporting services, agents often split their commissions fees with the associated brokerage firm on each transaction basis. In practice, brokerage firms often give a higher percentage of commissions to reward agents who complete in-house transactions (Gardiner, Heisler, Kallberg, and Liu, 2007).

Why would real estate brokerage firms have incentives to reward their agents for promoting in-house transactions? One possible reason is that a brokerage firm that promotes in-house transactions has a higher chance to capture commission fees from both ends than other firms.<sup>3</sup> In addition, by promoting in-house transactions, a brokerage firm can effectively increase its market share, thereby gaining an advantage in competing for the attention of future clients. Moreover, having an in-house transaction may help reduce transaction costs and speed up the search and/or negotiation process, hence improving transaction efficiency.<sup>4</sup> Since listing agents cannot freely compete in the commission fees they offer to cooperating agents, the in-house promotion bonus would create incentives for the cooperating (listing) agents to “steer” buyers (listings) toward internal listings (buyers).

## 3.2 A Model of Agent-Intermediated Search

### 3.2.1 The Setup

Our model of agents’ decisions to distort home matching process follows closely Hagiu and Jullien (2011), who provide the first economics analysis of search diversion in an online shopping setting. Similar to their approach of modelling search diversion, we show that agents can misguide homebuyers by introducing noise in the search process through which buyers find the houses that match their preferences the best. There are two key differences between our model and theirs. First, instead of assuming a fixed amount of revenues from each store visit, we assume that agents receive a fixed percentage of *realized* sales revenues and that this percentage is *bigger* when a transaction occurs within the same brokerage firm. Second, instead of assuming buyers’ values of different stores are independent/complementary/substituable, we assume that two houses are competing

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<sup>3</sup>Controlling for the number of agents, we find that brokerage firms with a higher fraction of in-house sales tend to have a larger number of total transactions, taking into account both ends of a transaction.

<sup>4</sup>Although this is likely to be true, our data show that, on average, time on the market for in-house transactions is actually longer than time on the market for cross-house sales.

directly with each other and that each buyer buys at most one house.

To simplify the analysis of the search process in the housing market, we assume that there are one cooperating agent, two types of buyers (1 and 2) and two types of houses (1 and 2).

**Buyers:** Buyers differ along two dimensions: preferences for houses and search costs. Along the first dimension, there are two types of buyers: type 1 buyers make up a fraction  $\alpha$  of the population and derive net utilities  $u^H$  from visiting house 1 and  $u^L$  from visiting house 2; type 2 buyers make up a fraction  $1 - \alpha$  of the population and derive net utilities  $u^H$  from visiting house 2 and  $u^L$  from visiting house 1. We assume that  $u^H > u^L$ , which implies that *ex ante* type 1 buyers prefer house 1 over house 2 and type 2 buyers prefer house 2 over house 1 in the sense that will be described below. Along the second dimension, buyers are differentiated by the search cost  $c$  they incur each time they visit a house. They can only visit at most two houses sequentially.

More specifically, take buyer 1 as an example. Her valuation of a specific house  $h$ ,  $v_h^1$ , is unknown prior to the visit but is learnt upon inspection of the house, so that the expected utility prior to visiting the house is  $u_h^1 = \int_{p_h}^k (v_h^1 - p_h) dG(v_h^1)$ , where  $G(v)$  denote the cumulative distribution of  $v$ ,<sup>5</sup>  $k = H$  if  $h = 1$  and  $k = L$  if  $h = 2$ . Assuming that  $0 < L < H$ , it follows that  $u_1^1 > u_2^1$ , which indicates that *ex ante* house 1 is a better match for buyer 1 than house 2. Note that  $u_h^1$  should be interpreted as encompassing the utility of just “looking around” the house plus the expected utility of actually buying from house, net of the price paid. Upon visiting a house, a buyer observes the realized value of being matched with a specific house,  $v_h^1$ , and then decides to whether to buy the house.

**Houses:** Houses also differ along two dimensions: quality of the match and the listing brokerage firm. Along the first dimension, as described above, type 1 house stands for houses that *ex ante* match the buyer 1’s preference best whereas house 2 stands for houses that *ex ante* match the buyer 2’s preference best. Along the second dimension, house 1 is listed by a firm that is different from the cooperating brokerage firm, whereas house 2 is listed by an agent affiliated with the same brokerage firm.

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<sup>5</sup> $v_1^1$  and  $v_2^1$  are assumed to be independently distributed for any given buyer.

For simplicity, we assume that prices of houses are exogenously given at  $p_1$  and  $p_2$ . This is because house prices are typically determined by general market conditions, which is much broader than the traffic that a specific cooperating agent brings. More importantly, the list price of a house is publicly advertised before the cooperating agents and their buyers are engaged in the search process. To the extent that the sale price and list price are highly positively correlated, the exogeneity assumption is justified.

**Cooperating Agent:** The cooperating agent observes each buyer’s type (1 or 2) but not her search cost  $c$ . Since the agent is assumed to have superior information about houses available in the market, he immediately knows which house *ex ante* fits the buyer’s preference best. Following Hagi and Jullien (2011), we denote by  $q_1$  the probability that the agent takes buyer 1 to house 1 for the *first* visit. If the cooperating agent always optimize the match process between buyers and houses, then we should expect  $q_1 = 1$ . In contrast, we say that the cooperating agent “strategically” promotes his own firm’s listings (i.e., house 2) whenever  $q_1 < 1$ .

The cooperating agent receives a fixed percentage of actual sales as commission income when a transaction is completed. This income is then split with the agent’s affiliated brokerage firm. In net, the cooperating agent obtains a fixed share of transaction price,  $\tau_1$  ( $\tau_2$ ), from the sale of house 1 (house 2, respectively). The key assumption here is since the cooperating brokerage firm benefits from double ends of an in-house transaction, it rewards the cooperating agents engaged in in-house transactions by giving them a larger share of commission fees. This implies that  $\tau_2 > \tau_1$ . As a result, the cooperating agent may sometimes find it profitable to recommend to buyer 1 house 2, which generates the highest revenue, rather than house 1, which matches buyer 1’s preference be best. The incidence of  $q_1 < 1$  captures precisely the inefficiency resulted from the commission structure described above.

**Timing:** The timing of decisions is as follows: (i) the agent publicly announces  $q_1$ ; (ii) buyers observe  $q_1$ ; (iii) buyers decide whether or not to follow agent’s guidance, engage in the search process, and make their purchase decisions after visiting the house(s).

### 3.2.2 Solving the model

Without loss of generality, let us focus our analysis on type 1 buyers first.

First consider a type 1 buyer with higher search cost, i.e.,  $c > u^H(p_1)$ . In this case, the buyer would not visit any of the two houses, and as a result, the agent receives zero commission income.

Second consider a type 1 buyer with low search cost, i.e., with  $c \leq u^L(p_2)$ . She will visit both houses irrespective of where the agent directs them for their first visit. Upon visiting both houses, the buyer compares two houses and purchases the one that gives her the largest net realized utility  $\max\{v_1 - p_1, v_2 - p_2\}$ . Accordingly, the probability of buyer 1 purchasing house 2,  $\rho_2^1$ , is given by:

$$\begin{aligned}\rho_2^1 &\equiv Pr(v_2^1 - p_2 > v_1^1 - p_1) \\ &= \int_{p_1}^H \int_{v_1^1 - p_1 + p_2}^L dG_L(v_2^1) dG_H(v_1^1) \\ &= \int_{p_1}^H (1 - G_L(v_1^1 - p_1 + p_2)) dG_H(v_1^1)\end{aligned}\quad (2)$$

Thus the cooperating agent receives commission income  $\tau_2 p_2$  with probability  $\rho_2^1$  and  $\tau_1 p_1$  with probability  $1 - \rho_2^1$ .

Finally consider a type 1 buyer with intermediate search costs, i.e.,  $u^L(p_2) \leq c \leq u^H(p_1)$ . In this case, if the buyer is first sent to house 1 (which happens with probability  $q_1$ ), she would make a purchase and stop visiting another house if the net realized value from buying house 1 ( $v_1 - p_1$ ) is greater than the expected utility of continuing visiting house 2 ( $\max\{u^L(p_2) - c, 0\}$ ) (which occurs with probability 1 given that  $u^H > u^L$ ). If she is first sent to house 2 (which happens with probability  $1 - q_1$ ), she would stop searching if and only the net realized utility ( $v_2 - p_2$ ) is greater than the expected utility of continuing visiting house 2 ( $\max\{u^H(p_1) - c, 0\}$ ).

Knowing probability  $q_1$ , a type 1 buyer follows the agent's guidance if her search cost is above  $u^L(p_2)$  and below some critical value  $u_1$ , where  $u_1 = c$  is implicitly defined by

$$q_1 u^H(p_1) + (1 - q_1) \int \max(v_2 - p_2, u^H(p_1) - c) g_L(v_2) dv_2 - c = 0 \quad (3)$$

Note that when  $q_1 = 1$ , we have  $u_1 = u^H(p_1)$  and  $\frac{du_1}{dq_1} = u^H(p_1) - u^L(p_2)$ .

Turning to the agent's side, the revenue he derives from type 1 buyers is then:

$$\begin{aligned} \Pi_1 = & (\tau_1 p_1 (1 - \rho_2^1) + \tau_2 p_2 \rho_2^1) F(u_L) + q_1 \tau_1 p_1 (F(u_1) - F(u_L)) \\ & + (1 - q_1) \left( \tau_1 p_1 \int_{u^L}^{u_1} G_L(p_2 + u^H - c) f(c) dc + \tau_2 p_2 \int_{u^L}^{u_1} (1 - G_L(p_2 + u^H - c)) f(c) dc \right) \end{aligned} \quad (4)$$

The first term represents the revenue that the agent receives from type 1 with low search costs, i.e., with  $c \leq u^L(p_2)$ . The second term represents the revenue that the agent receives from type 1 buyers who have intermediate search costs, i.e., with  $u^L(p_2) \leq c \leq u_1$ , and have been efficiently matched to house 1 on their first visit. The third term represents the revenue that the agent receives from type 1 buyers who have intermediate search costs but have been strategically directed to house 2 first. Note that the first integrant term is the probability that the buyer decide to continue searching conditional on housing visited house 2 in the first round of search.

Maximizing (2) over  $q_1$  yields the following proposition, which contains our baseline results:

**Proposition 1** *The cooperating agent “strategically” promotes in-house transactions (by showing house 2 to buyer 1 with intermediate search costs – i.e.,  $u^L(p_2) \leq c \leq u_1$  – in her first round of search) if and only if*

$$\frac{\tau_2 p_2}{\tau_1 p_1} > \frac{F(u^H) - F(u^L) - \int_{u^L}^{u_1} G_L(p_2 + u^H - c) f(c) dc + f(u^H)(u^H - u^L)}{F(u^H) - F(u^L) - \int_{u^L}^{u_1} G_L(p_2 + u^H - c) f(c) dc} \quad (5)$$

**Proof:** The cooperating agent maximizes (4) over  $q_1$ . Using the fact  $u_1(q_1 = 1) = u^H(p_1)$  and  $\frac{du_1}{dq_1}(q_1 = 1) = u^H(p_1) - u^L(p_2)$ , it is straightforward to show that  $\frac{\partial \Pi_1}{\partial q_1}(q_1 = 1) < 0$  if and only if (5) holds. ■

### 3.2.3 Strategic in-house transactions

Condition (5) is central to understanding of agents' incentives to strategically promote in-house transactions. In particular, at  $q_1 = 1$ , all type 1 buyers with intermediate search costs will be first directed to houses that match their preference best, leading to an efficient matching outcome. By laying out conditions under which the cooperating agent lowers  $q_1$  below 1, condition (5) immediately delivers three key sources of strategic in-house transactions.

First, the commission structure matters. It is clear from condition (5) that the optimal amount of strategic promotion increases with the ratio  $\frac{\tau_2 p_2}{\tau_1 p_1}$ . Given the commission structure specified above,

we would expect  $\tau_2 > \tau_1$  for type 1 buyers. So if the prices of two houses are not too different from each other (which is not too unreasonable given that buyers usually specify a price range for houses they search for), the larger is the ratio  $\frac{\tau_2}{\tau_1}$ , the more likely condition (5) will hold, and the stronger is the agent’s incentive to promote his own firm’s listings. While the commission rate is typically set at 2.5%, some listing agents would offer higher or lower rate to cooperating agents.<sup>6</sup> Intuitively, by rewarding cooperating agents a greater proportion of the commission, a listing agent can effectively increase  $\tau_1$  in condition (5), and this helps offset the in-house transaction incentives offered to the cooperating agent by his affiliated brokerage firm. Conversely, when the commission rate offered by a listing agent is low, cooperating agents are more likely to respond to the financial incentives offered by the brokerage firm for promoting in-house transactions. Thus, we expect that lower commission rates offered to cooperating agents are associated with a stronger presence of strategical in-house transactions.

Second, the extent to which cooperating agents can promote in-house transactions depends on the difference in the matching quality that a given buyer obtains from internal and external listings. In condition (5), this is reflected by a bigger  $(u^H - u^L)$  on the right hand side, and a smaller likelihood of strategic promotion ( $q_1 < 1$ ). Intuitively, when a buyer’s most ideal house is far better than the best house that the buyer can find from internal listings, it becomes difficult for her agent to “strategically” promote internal own listings. Empirically, we do not observe matching quality. However, housing markets are characterized by increasing returns to scale (Genesove and Han, 2012). When a brokerage firm has a larger number of listings that a buyer can choose among, there should be less dispersion in the buyer’s valuation of her most-preferred house from the market-wide pool and from the internal listings. As a result, the brokerage firm will find it easier to promote its own listings.

Third, the brokerage firm’s ability to influence individual buyers’ choice set also depends on buyers’ search cost. As is clear in equation (4),  $q_1$  only affects the revenue that an agent receives from buyers with intermediate search cost ( i.e., with  $u^L(p_2) \leq c \leq u_1$ ), but not the revenue he

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<sup>6</sup>Commission rates offered to cooperating agents are normally advertised in the MLS when properties are listed, and they tend to remain the same until the final transactions.

receives from buyers with low search cost (i.e., with  $c < u^L(p_2)$ ). The latter type of buyers will visit all houses regardless of the agents' recommendations, leaving no room for agents to create a biased selection of potential matches. In practice, it is reasonable to assume that local buyers have lower search costs than out-of-town buyers, and that those who search during the summer have lower search costs than those during the winter. Thus, we expect that buyers with low search cost are less likely to be affected by agents' strategic promotions.

Finally, the brokerage firm's ability to strategically promote in-house transactions also depends on whether buyers are aware of agents' incentives to strategically promote. So far, the model has assumed that buyers faced with a known probability of  $q_1$ . If buyers are not aware of agents' strategic incentives, this would remove the dependence of  $\frac{du_1}{dq_1}$  in deriving the derivative of  $\Pi_1$  with respect to  $q_1$ . As a result, the right-hand-side of Condition (5) is reduced to 1. In this case, the agent's incentive to promote in-house transactions would purely depend on the financial reward ( $\frac{\tau_2}{\tau_1}$ ) and search cost. The quality difference would no longer matter, since buyers believe that agents always match them to their first best house and hence would not be sensitive to the difference between the first and second best houses ( $u^H - u^L$ ). As discussed later, our sample covers a natural experimental opportunity permitted by a legislation that required real estate agents engaged in in-house transactions to disclose this fact to both buyers and sellers. This allows us to empirically examine the strength of strategic promotions in a setting where it is undisclosed and then, after the legislation, in a situation where market participants are aware of the dual agency relationship.

### 3.2.4 Efficient in-house transactions

In-house transactions could also occur for efficiency rather than incentive reasons. In our model, the probability of non-strategic in-house transactions is given by:

$$P = (\alpha\rho_2^1 + (1 - \alpha)(1 - \rho_1^2)) F(u_L) + \alpha q_1 (F(u_1) - F(u_L)) + (1 - \alpha)(F(u_2) - F(u_L)) \quad (6)$$

The first term refers to the probability of in-house transactions by type 1 and type 2 buyers with low search costs. With probability  $\rho_2^1$ , a type 1 buyer purchases house 2 because house 2 delivers larger net realized utility than house 1. Similarly, with probability  $1 - \rho_1^2$ , a type 2 buyer

purchases house 2. In both cases, transactions occur within the same brokerage firm, and these in-house transactions represent an outcome of buyers' own choice rather than agents' promotional effort. In particular, the low search cost removes the reliance of buyers on agents in looking for ideal homes, resulting in an efficient match between buyers and houses, regardless whether the transaction occurs within the same brokerage house or not.

The second term refers to the probability of in-house transactions by type 1 buyers with intermediate search cost, while the third term refers to the probability of in-house transactions by type 2 buyers with intermediate search cost. It is straightforward to show that with probability  $q_2 = 1$ , all type 2 buyers will be first directed to house 2.<sup>7</sup> In this case, the agents' incentive to promote their own listings is consistent with the buyers' interest, because these listings match the buyers' preference best. This type of in-house transactions, although promoted by cooperating agents, represents an efficient matching outcome.

Thus, the model predicts two types of efficient in-house transactions. Since the first type of in-house transactions is not driven by agents, we focus our discussion on the last type of in-house transactions, which is driven by mutual interests of buyers and their agents. An increase in  $(1 - \alpha)$  increases the fraction of buyers who prefer houses listed by the same brokerage firm over houses listed by a different brokerage firm, and hence the probability of the second type of efficient in-house transactions. In practice, buyers prefer houses listed by the same brokerage firm for various reasons. For example, an in-house transaction may lower transaction costs and improve the efficiency in the bargaining and closing stage, making buyers more likely to favour transactions within the same brokerage house. Alternatively, a buyer may choose a cooperating agent simply because the agent's affiliated firm specializes in listing houses that fit the buyer's interest best. For example, some brokerage firms have information advantage about neighborhood and property characteristics in certain geographical locations. Others may specialize in selling expensive houses or newly built

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<sup>7</sup>To see this, note that for type 2 buyers, Condition (5) can be re-written as:  $\frac{\tau_1 p_1}{\tau_2 p_2} > \frac{F(u^H) - F(u^L) - \int_{u^L}^{u^1} G_L(p_2 + u^H - c)f(c)dc + f(u^H)(u^H - u^L)}{F(u^H) - F(u^L) - \int_{u^L}^{u^1} G_L(p_2 + u^H - c)f(c)dc}$ . Assuming houses 1 and 2 are in the same price range. In this case, the left-hand-side is less than 1, while the right-hand-side is greater than 1. This implies that the threshold condition will never be met, and hence  $q_2 = 1$ .

homes.<sup>8</sup> Together, these brokerage firms may attract buyers with strong preferences for housing market segments in their areas of specialization, and hence create information efficiencies for the buyers they represent.

In sum, there are a number of brokerage- and property-specific features that can be tied to predictions about in-house transactions. These range from measures of strategic promotion to measures of brokerage specialization. In the empirical work below, our goal is to distinguish between these two types of influences and to evaluate whether in-house transactions create any distortion to the home transaction process that benefits agents themselves rather than buyers and sellers.

## 4 Data and Descriptive Statistics

The main source of our data is the Multiple Listing Service (MLS) in a large North American metropolitan area from January 2001 to December 2009. Our sample covers 28 districts, which comprise a third of the metropolitan area studied in this paper. There are over 200,000 transactions and more than 1,000 brokerage firms. The MLS data contain detailed information on house characteristics, including the number of bedrooms, the number of washrooms, lot size, the primary room size, dummy variables for basement, garage space and occupancy. In addition, the data provide neighborhood information, listing and transaction price, as well as real estate brokerage firms on both sides of a transaction. Properties are identified in the MLS data by district, MLS number, address, unit number (if applicable).

The focus of this paper is in-house transactions. We consider two types of in-house transactions. The first is a brokerage-level in-house transaction for which the cooperating agent and the listing agent are associated with the same brokerage. The second is a franchise-level in-house transaction for which the cooperating brokerage and the listing brokerage in the transaction are affiliated with the same franchise. In this paper, in-house transactions mostly refer to the first type, but we also consider franchise-level in-house transactions in this section.

Tables 1-5 present the patterns in both brokerage-level and franchise-level in-house transactions

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<sup>8</sup>The former occurs if firms have developed expertise in marketing luxury homes; the latter occurs if firms have cultivated relationships with developers and contractors.

across various characteristics. Table 1 shows the fraction of in-house transactions by real estate brokerage franchises. We combine all transactions carried out by cooperating brokerages affiliated with each franchise, and compute the fraction of in-house transactions for each franchise. The fraction of in-house transactions is relatively higher for Re/Max, Royal LePage, Prudential, and MinCom. The table also shows that the leading franchises (in terms of total share) do not necessarily have higher fractions of in-house transactions. Homelife, for example, has a lower percentage of in-house transactions than independent brokerage firms. The table thus suggests that franchise-affiliation might partially account for variations in in-house transactions.

Tables 2-4 report the fraction of in-house transactions by brokerage size. In Table 2, we rank cooperating brokerages in order of their total market shares in our data, and group them by their rankings.<sup>9</sup> In Table 3, we group cooperating brokerages by the number of real estate agents, while in Table 4, we group them by the number of offices. All three tables show that larger brokerages tend to have relatively higher fractions of in-house transactions.

Table 5 shows a slight downward trend in the later years for in-house transactions in our sample. One possibility is that if strategic promotion is an important source of in-house transactions, this downward trend suggests that the effect of strategic promotion might have been partially weakened by the enforcement of the REBBA legislation in 2006. We will investigate this possibility in Section 5.

## 5 Testing the Model's Predictions

### 5.1 Testing the Effects of Commission Structures

To examine the presence of strategic in-house transactions, we start with estimating the effect of commission fees on the incidence of in-house transactions. We create two dummy variables that reflect the commission fees. The first is a dummy variable that equals one if the commissions received by the cooperating agent from the listing agent in a given transaction are less than 2.5% of house price. A lower commission split makes the self-promotion bonus offered by the brokerage

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<sup>9</sup>An interesting observation not reported in the table is that top 20 cooperating brokerages do not include any independent brokerage, and among top 100 firms, more than 90% are franchisees, which suggests potential importance of franchise brand or brand recognition in this industry.

firm more attractive, leading to a stronger presence of strategic in-house transactions.

The second is a dummy variable that equals 1 if the cooperating agent splits commission fees with the brokerage firm on per-transaction basis. As described earlier, some brokerage firms paying their agents a percentage of commission fees for each transaction rather than letting the agents keep 100% commission fees. The revenues from this type of firms strictly increases with the number of either side of transactions. And as a result, these firms are more likely to offer self-promotion bonus to agents, leading to a stronger presence of strategic in-house transactions.

To test these hypotheses, we estimate the incidence of in-house transactions as a function of two commission variables, controlling for housing attributes, listing price, location, year and month of the transaction, and the number of listings owned by the cooperating brokerage. Housing attributes include lot front, lot depth, the length and width of the primary room, dummy variables for basement, garage space and occupancy. Eight slightly different versions are estimated, and results are reported in Table 6. Column 1 presents the baseline results. The coefficients on both commission dummies are positive and significant, consistent with what the model implies. In particular, receiving lower commission fees from the listing agent increases the probability of in-house truncations by 11%, while splitting fees with the office on per-transaction basis increases the probability of in-house transactions by 1%. Together, these estimates provide strong evidence for the presence of in-house transactions due to strategic promotions.

Despite our rich control of housing attributes, one might be concerned that unobserved house quality could vary so much to render the estimates imprecise. Fortunately, we have tax assessments for the year of, or the year prior to listing. Since taxes are a constant percentage of assessed value, taxes is a perfect proxy for assessed value, which contains the information observed by agents and buyers but not by the econometrician. As a control for the unobserved housing attributes, in Column 2, we add taxes, along with the year when taxes are assessed. The coefficients on the two commission variables remain the same, both in magnitude and in significance. This is perhaps not surprising, as the listing price of the house, which has already been controlled in the baseline specification, usually contains a lot of information about unobserved house attributes, including

the previous year's tax assessment value.

As a further control for unobserved house attributes, we also restrict the sample to houses that were sold multiple times in our sample period. Doing so allows us to control for house fixed effects. Columns 3-4 of Table 6 present the results. The coefficient on the low-commission dummy is increased slightly to 0.12, which is significant at the 5% level, regardless whether taxes are controlled or not. On the other hand, the estimates on per-transaction-split become small and insignificant.

As our model implies, in-house transactions could occur for efficiency rather than incentive reasons. For example, when a brokerage has superior information about properties and buyers' demand curve in a specific housing market segment, an in-house transaction can arise as an efficient matching outcome. In the remaining columns, we control for brokerage specialization by adding the interactions of brokerage firm dummies with neighbourhoods (Columns 5-6) and with price ranges (Columns 7-8).<sup>10</sup> The former are intended to control for specialization based on geographical areas, while the latter for specialization based on certain price ranges. The effect of the low commission dummy continues to be positive and strong, with a 10.1% increase in the probability of in-house transactions when geographical specialization is controlled, and a 9.8% increase when price range specialization is controlled. On the other hand, since the per-transaction-split dummy is a firm-specific policy variable, we can no longer estimate the effect of the per-transaction-split alone. However, as discussed shortly, this effect will be recovered again when we restrict our attention to low search cost buyers.

A comparison of Columns (5)-(8) with Columns (1)-(2) also reveals that adding interactions of brokerage dummy with geographical areas and price ranges increases the  $R^2$  by almost one-third, indicating that brokerage specialization indeed plays an important role in in-house transactions. However, controlling for brokerage specialization does not seem to weaken the effect of commission incentives on strategic in-house transactions.

Another efficient source of in-house transactions comes from transaction cost savings. In partic-

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<sup>10</sup>We use price.300-400, price.400-500, price.500-1000, and price.1000+, where price.300-400 is the dummy for whether the sales price is between \$300,000 and \$400,000.

ular, having the same agency representing both sides of a transaction may reduce transaction costs within the firm and give firm additional incentives to promote their own listing. To the extent this is true, one might doubt the exogeneity assumption of the commission variables. We presents three pieces of evidence to show that this is unlikely to be a concern. First, an investigation of our data shows that, on average, in-house transactions takes longer time on the market than cross-house transactions, which suggests that firms are unlikely to save substantially in transaction costs just by promoting in-house sales. Second, to the extent that some firms may set their commission fees to lower transaction costs, such effect would have been controlled by the inclusion of the brokerage firm fixed effects in Columns (5)-(8). Finally, as shown in Section 5.3, we will further exploit an exogenous variation permitted by a legislation to address this concern. The legislation constrains agents' ability to strategic promote internal listings, but is unlikely to affect other types of in-house transactions.

Finally, we expect that the size of a brokerage firm matters for in-house sales for at least two reasons. First, larger firms are more likely to possess a listing that matches a buyer's preference better, making the buyer put less value on the market-wide pool of listings. Second, if in-house sales indeed help enhance search efficiency, liquidity theory suggests that such benefits are bigger for larger firms. To test these effects, we control for the number of listings owned by the cooperating brokerage in the month of transaction in all Columns (1)-(8). Table 6 indicates that having 100 additional listings increases the probability of in-house transactions by roughly 7 – 10%. The strong positive and statistically significant effects are consistent with what we have expected.

## 5.2 Testing the Effects of Search Costs

A second prediction of the model is that the brokerage firm's ability to influence individual buyer's choice set depends crucially on the cost that occur for buyers if they search for houses on their own. In particular, the commission structure should matter for in-house transactions only when buyers have relatively higher search costs if they were to search houses on their own. To construct a measure of search costs, we construct a dummy variable that equals one if the house is in an area without easy subway access. In the sample city under investigation, the public transit commission operates

an extensive system of subways, which is further linked with buses and streetcars. Together, it covers 1,200 km (750 mile) of routes and heavily used by people who live in or near the city.<sup>11</sup> Thus, if a house is located in an area without easy subway access, the cost of buyers searching for the house on their own would presumably be higher.

To test this, we expand the specifications in Table 6 by including interactions between no-subway dummy and commission structure variables. The results are reported in Table 7.

Column (1) of Table 7 presents the baseline estimates when we control for house attributes, listing price, house location, transaction period, and broker listings. We find that the commission structure variables alone do not have strong positive and significant effects as in Table 6. This suggests that for buyers with easy subway access and hence low search costs, there is less room for agents to strategically guide their choice in the screening and decision stage even when agents have financial incentive to do so. In contrast, the coefficient on the interaction of low-commission dummy and no-subway dummy is 0.11, while the coefficient on the interaction of per-transaction-split dummy and no-subway dummy is 0.01. Both estimates are positive and statistically significant, providing evidence for agents' promotion of in-house listings to high search cost buyers. Together, these results are consistent with what the model implies, that is, the incidence of strategic in-house transactions depends not only on agents' financial incentives, but also on their ability to influence buyers' decision.

To control for unobserved house attributes, in Columns (2)-(4), we further control for taxes and/or house fixed effects. In Column (2) where taxes are controlled, the coefficient on the commission variables remain the same as in Column (1). Restricting transactions to repeated sales properties reduces the sample size by over a half but allows us to control for house fixed effects. In this case, the coefficient on the low-commission dummy becomes 0.2 while the coefficient on the per-transaction-split dummy becomes 0.04, regardless whether taxes are controlled (Columns 3-4). These estimates are significant at the 5% level.

Columns (5)-(8) provide further controls of brokerage specialization. As explained earlier, this

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<sup>11</sup>The city has the third highest transit system ridership in North America.

prevents us from including the per-transaction-split dummy by itself. However, its effect on low search cost buyers (those without easy subway access) can still be identified. In Column (5) where we control for brokerage specialization based on geographical areas, receiving lower commissions increases the probability of in-house transactions by 11% for high search cost buyers and almost none for low search cost buyers; similarly, splitting commission fees with office on per-transaction basis increases the probability of in-house transactions by about 1.4% for high search cost buyers. Together, these estimates are highly consistent with what we would expect. Adding taxes (Column 6) does not change these estimates in any noticeable way. Controlling for brokerage specialization based on house price ranges (Column 7) increases the coefficient on the low-commission dummy slightly further, but the coefficient on the per-transaction-split dummy becomes insignificant. Adding taxes (Column 8) again does not make any noticeable difference in this case.

Together, these estimates confirm the model's prediction that agents' ability to promote in-house listings depends crucially on buyers' search cost. The evidence remains robust even after we control for unobserved house heterogeneity and brokerage specialization based on geographical areas.

### **5.3 Testing the Effects of REBBA**

A third prediction of the model is that buyers are more concerned with the quality difference between the internal and external pool of listings when they are more aware of agents' strategic incentives. While we do not observe the match quality directly, a brokerage with a larger number of listings is likely to own a listing that is closer to a buyer's ideal house. Thus one can infer about the effect of match quality difference on in-house transactions from the the coefficient on the number of listings. However, as discussed earlier, one problem with this interpretation is that a positive coefficient is also consistent with the hypothesis that larger firms save more in transaction costs from promoting their own listings.

To test the effects of match quality, we thus exploit a natural experimental opportunity permitted by the Real Estate and Business Brokers Act (REBBA), a legislation that was implemented by in March 2006 and required real estate agents engaged in in-house transactions to disclose this fact

to both buyers and sellers. The purpose of the legislation is to help consumers avoid undisclosed and unintended dual agency relationship. This legislation should affect in-house sales only through agents' strategic promotion but not through other channels. So if we indeed find stronger effects of the number of listings on in-house transactions after the legislation, this would provide evidence for the third prediction from the model.

In Table 8, we expand the earlier specifications and interact the REBBA dummy with the number of listings, commission measures, and search cost variables. In Column 1 where house attributes, listing price, location and transaction period are controlled, the coefficient on the number of listings is 0.082, and the coefficient on the interaction of REBBA with the number of listings is 0.008, both coefficients are significant at the 1% level. This means that for a given brokerage firm, having 100 additional listings in the buyer's search range would increase the chance of in-house sales by 8%, and that such effect is further increased to 9% after the REBBA was implemented. These estimates are consistent across different specifications with a variety of controls. The result confirms the hypotheses that buyers care about the match quality difference between the internal and external listings, and that such difference matters more when agents become more aware of the agent's strategic incentives.

The enforcement of the REBBA also provides an additional source of exogenous variation that helps us identify the strategic promotion effect. In particular, using the enforcement of the REBBA as an instrument, we can obtain a difference-in-difference estimate on how the commission incentives affect the probability of in-house sales before and after the regulation. To see this, note that we have included a triple interaction term among the REBBA dummy, the subway dummy and the commission variables. In the baseline specifications (Columns 1-2), the coefficients on these triple interaction terms are small and insignificant, suggesting that the effect of REBBA on agents' ability to promote in-house listings is negligible. These results are robust when we restrict the sample to repeated sale properties and control for house fixed effects (Columns 3-4). However, this pattern no longer holds once we add controls for brokerage specialization. In Column (5) we control for brokerage specialization based on geographical areas. The estimates show that receiving low

commissions increases the probability of in-house transactions by 14% for low search cost buyers, but such effect is reduced by over a half after the implementation of REBBA. Both effects are strong and statistically significant, consistent with what we expect. This result is robust when we control for taxes (Column 6) and specialization based on price ranges (Columns 7-8). On the other hand, splitting the commissions on per-transaction basis does not seem to have significant effects on in-house sales, both before and after the implementation of the REBBA. This could be because the commission structure variable is firm-specific and its main effect has already been absorbed the inclusion of the brokerage fixed effects.

Together, these estimates provide additional support for the role of agents' strategic incentives in promoting in-house listings. They also suggest that agents did react to the implementation of the REBBA. Before the regulation, agents have more ability to steer their buyer clients toward their internal listings. After the regulation, such effect is reduced by a great extent. However, it is worth noting that the implementation of the REBBA did not completely eliminate agents' ability to promote in-house sales. One possible reason is that the REBBA makes the inherent incentive conflict problem associated with in-house sales acknowledged, but not resolved. Another possible reason is that the difficulty of monitoring the information that agents reveal to their clients could result in a weaker enforcement of the legislation than expected, making the disclosure policy less effective. Nevertheless, our findings on the weakened effect of commission variables on agents' strategic promotion, along with the findings on buyers' increasing sensitivity to the difference between internal and external listings, suggest that the REBBA legislation was warranted and had some desired effects.

## **6 Structural Model**

So far we have obtained a set of findings that are consistent with the model's predictions. While the results provide strong evidence for the presence and determinants for the strategic promotions, they cannot tell us the size of the strategic promotion in explaining in-house transactions. They also cannot help us evaluate the welfare change under the the legislation that required agents

engaged in in-house transactions to disclose the dual agency relationship to consumers. For these reasons, we develop a structural model of housing choice that incorporates both benefits and costs associated with in-house transactions. Doing so allows us to evaluate the economic impact of strategic promotions as well as understanding the welfare consequence of such policy changes. This section first presents our structural model, and then describes our estimation approach.

## 6.1 Structural Model for Housing Choice

Our structural model builds on the approach developed by Bajari and Benkard (2005) and Bajari and Kahn (2005) who improve upon the hedonic two-step approach of Rosen (1974) and Epple (1987) by incorporating a nonparametric estimation for the hedonic price function. We further extend their model by considering efficient matching and strategic promotion to explain in-house transactions.

To describe the model, let us consider market  $t \in T$ , where there are  $i = 1, \dots, I_t$  home buyers who are looking for houses, and  $j = 1, \dots, J_t$  housing units that sellers put on the market. The interactions of a large number of buyers and sellers will lead to hedonic equilibrium in which buyers match to houses, and the resulting equilibrium prices are determined by the hedonic price function that maps housing characteristics to prices as follows:

$$p_j = \mathbf{p}_t(X_j, \xi_j), \tag{7}$$

where  $p_j$  is the sales price of house  $j$ ,  $X_j$  is a  $1 \times m$  vector of observed attributes of house  $j$ ,  $\xi_j$  is the unobserved house characteristics, and  $\mathbf{p}_t$  is the price function in market  $t$  that varies across different markets, reflecting different equilibrium in each market.

Because our goal is to recover a buyer's preferences, we focus on the buyer's problem. We posit that buyers' utility functions are defined over house characteristics  $X_j$  and  $\xi_j$ , as well as the composite commodity denoted by  $e$ . The buyer's problem is to maximize her utility  $u_i(X_j, \xi_j, e)$  subject to the budget constraint. We assume that the budget constraint is given by

$$e + p_j + g_i(d_j) = y_i, \tag{8}$$

where the price of the composite commodity is normalized to one,  $y_i$  is buyer  $i$ 's income,  $d_j$  is the indicator variable for whether house  $j$  is listed by the same brokerage as a buyer's cooperating brokerage, and  $g_i(d_j)$  is buyer  $i$ 's implicit cost associated with  $d_j$ .

Note that we include  $g_i(d_j)$  in (8) to allow for two possibilities related to in-house transactions. First, if in-house transactions reduce transaction costs associated with home buying process, the resulting cost saving will be reflected in  $g_i(d_j)$ . Specifically, we assume that in-house transactions may reduce transaction costs by  $\gamma_i$ . Second, if buyer  $i$ 's cooperating agent is engaged in strategic promotion, the agent will promote only houses listed by the same brokerage, and will be less likely to show houses listed by other brokerages even if they may fit the buyer's preferences. To model this possibility, we assume that if buyer  $i$  faces strategic promotion, the implicit cost of visiting houses listed by other brokerages will increase by  $c_i$ .<sup>12</sup> This assumption implies that the buyer's choice set will remain the same even under strategic promotion, but that choosing houses listed by other brokerages will become more costly. Combining these assumptions, we obtain

$$g_i(d_j) = -\gamma_i d_j + c_i(1 - d_j), \quad (9)$$

where  $\gamma_i$  and  $c_i$  are random coefficients unique to each buyer.

After substituting the budget constraint into the utility function, we can write the buyer's maximization problem as

$$\max_j u_i(X_j, \xi_j, y_i - \mathbf{p}_t(X_j, \xi_j) - g_i(d_j)). \quad (10)$$

Following Bajari and Benkard (2005) and Bajari and Kahn (2005), we impose a functional form assumption for identification of the utility function. Specifically, we assume the linear utility function given by

$$u_i(X_j, \xi_j, e) = \sum_{k=1}^m \beta_{i,k} x_{j,k} + \beta_{i,0} \xi_j + e \quad (11)$$

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<sup>12</sup>Alternatively, we could model strategic promotion by restricting the buyer's choice set. However, this would lead to the discrete choice model with random choice sets, given that we do not observe the actual choice set considered by each buyer. Such a model would require heavy computations, because a large number of houses means that there are too many choice sets to consider.

where  $\beta_i = (\beta_{i,0}, \dots, \beta_{i,m})$  is a vector of buyer-specific random coefficients capturing buyer  $i$ 's preferences for housing characteristics.

Suppose that house attribute  $x_{j,k}$  is a continuous variable and that there is an interior maximum for the buyer's utility maximization problem. Given the utility function in (11), we can then derive the first-order condition with respect to  $x_{j,k}$  as follows

$$\beta_{i,k} = \frac{\partial \mathbf{p}_t(X_{j^*}, \xi_{j^*})}{\partial x_{j,k}}, \quad (12)$$

where  $j^*$  denotes the house that solves the buyer's problem in (10). The equation in (12) suggests that if we recover the slope of the price function in a local neighborhood of  $(X_{j^*}, \xi_{j^*})$ , then we can also recover buyer  $i$ 's random coefficient  $\beta_i$ . Bajari and Benkard (2005) and Bajari and Kahn (2005) build upon this insight and propose an approach based on a nonparametric estimation of the price function, which we also use in this paper.

With respect to  $d_j$ , we cannot obtain similar equation as (12), because  $d_j$  is a discrete variable and the price function does not depend on  $d_j$ .<sup>13</sup> Nevertheless, we can derive inequality constraints with respect to  $d_j$ . To this end, let us first define

$$U_j(\beta_i) = \sum_{k=1}^m \beta_{i,k} x_{j,k} + \beta_{i,0} \xi_j - \mathbf{p}_t(X_j, \xi_j),$$

so that  $u_i(X_j, \xi_j, y_i - \mathbf{p}_t(X_j, \xi_j) - g_i(d_j)) = U_j(\beta_i) + y_i - g_i(d_j)$ , given the utility function in (11).

If buyer  $i$  chooses house  $j^*$  with  $d_{j^*} = 1$ , then it must be that

$$U_{j^*}(\beta_i) + y_i + \gamma_i \geq U_s(\beta_i) + y_i - c_i, \quad \forall s \in D_t^0,$$

where  $D_t^0$  denotes a set of houses sold through cross-house transactions in market  $t$ . Since buyer  $i$  has chosen house  $j^*$ , the buyer can observe  $U_{j^*}(\beta_i)$ . However, given that a large number of houses are normally available in the market, it is unlikely that the buyer can observe  $U_s(\beta_i)$  for all houses from cross-transactions. Therefore, a more plausible decision rule is that buyer  $i$  chooses  $d_{j^*} = 1$  if

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<sup>13</sup>The hedonic price function is a function of house characteristics, whereas  $d_j$  is not a pure housing attribute. Nevertheless, in-house transactions due to either efficient matching or strategic promotion may also affect equilibrium prices, and so we could include  $d_j$  in the hedonic price function. We will consider this extension in the future, but given that  $d_j$  may be also affected by housing prices, we need to address the endogeneity issue, for example, by using the instrumental variable approach proposed by Bajari and Benkard (2005).

$U_{j^*}(\beta_i) + y_i + \gamma_i \geq E[U_s(\beta_i) + y_i - c_i | d_s = 0]$ , that is,

$$U_{j^*}(\beta_i) + \gamma_i \geq E[U_s(\beta_i) | d_s = 0] - c_i. \quad (13)$$

Similarly, buyer  $i$  chooses  $d_{j^*} = 0$  if

$$U_{j^*}(\beta_i) - c_i > E[U_s(\beta_i) | d_s = 1] + \gamma_i. \quad (14)$$

Therefore, the decision rules in (13) and (14) provide the inequality constraints with respect to  $d_j$ .

If we recover  $\beta_i$  from the first-order conditions in (12), we can compute  $U_{j^*}(\beta_i)$  using the actual choice of buyer  $i$ . In contrast,  $E[U_s(\beta_i) | d_s = 0]$  and  $E[U_s(\beta_i) | d_s = 1]$  cannot be computed directly by using the recovered  $\beta_i$ . But given  $\beta_i$ , we can recover  $U_s(\beta_i)$ ,  $\forall s \neq j^*$ , and so we may obtain the expected value by computing the mean of recovered  $U_s(\beta_i)$ . However, this naive approach entails two issues. First, the recovered  $U_s(\beta_i)$  may not be reliable if the characteristics of house  $s$  are very different from the characteristics of house  $j^*$ , since  $\beta_i$  is locally identified. Second, the buyer who purchased house  $j^*$  with characteristics  $X_{j^*}$  is likely to be more interested in houses with similar characteristics as  $X_{j^*}$  and less interested in houses with different characteristics. Therefore, when we compute the expected value  $E[U_s(\beta_i) | d_s = 0]$  or  $E[U_s(\beta_i) | d_s = 1]$ , we need to put more weights on the houses with similar characteristics as house  $j^*$  and less weights on those with different characteristics. For this reason, we use econometric matching techniques (e.g. Heckman, et al. 1997, 1998) to estimate  $E[U_s(\beta_i) | d_s = 0]$  and  $E[U_s(\beta_i) | d_s = 1]$ . Section 6.2 describes our estimation approach in detail.

Once we recover  $U_{j^*}(\beta_i)$ ,  $E[U_s(\beta_i) | d_s = 0]$ , and  $E[U_s(\beta_i) | d_s = 1]$ , the inequalities in (13) and (14) provide bounds on  $\gamma_i$  and  $c_i$ . We could estimate such bounds using the bounds approach proposed by Bajari and Benkard (2005). In this paper, we instead follow Bajari and Kahn (2005) and impose a parametric assumption to obtain point identification. Specifically, we combine the inequalities in (13) and (14), and consider the following inequality:

$$d_{j^*} = 1 \quad \text{iff} \quad V^1(\beta_i) - V^0(\beta_i) + \delta_i \geq 0, \quad (15)$$

where we use  $\delta_i$  to denote  $\gamma_i + c_i$ , and  $V^1(\beta_i) = d_{j^*} \times U_{j^*}(\beta_i) + (1 - d_{j^*}) \times E[U_s(\beta_i) | d_s = 1]$ , whereas  $V^0(\beta_i) = (1 - d_{j^*}) \times U_{j^*}(\beta_i) + d_{j^*} \times E[U_s(\beta_i) | d_s = 0]$ .

The inequality in (15) shows that we can recover the distribution of  $\delta_i = \gamma_i + c_i$  if we impose a parametric assumption on the distribution of  $\gamma_i$  and  $c_i$ . Moreover, if we use exclusion restrictions in that a certain variables only affect  $c_i$ , not  $\gamma_i$ , then we can estimate the marginal effect of strategic promotion on the probability of in-house transaction.

## 6.2 Estimation

To estimate our model, we follow and modify the estimation approach used by Bajari and Kahn (2005) which involves three steps. The first step estimates the hedonic price function using nonparametric methods. In the second step, we recover buyer-specific utility parameters  $\beta_i$ , and estimate  $V^1(\beta_i)$  and  $V^0(\beta_i)$ . In the third step, we estimate the distribution of  $\gamma_i$  and  $c_i$ . In what follows, we describe our approach in detail. We also provide discussion on identification where applicable.

### 6.2.1 Step 1: estimating the price function

In the first step, we recover the slope of the price function in a local neighborhood of  $(X_{j^*}, \xi_{j^*})$ , that is, the characteristics of house  $j^*$  chosen by buyer  $i$ . To this end, we use a nonparametric estimation of the hedonic price function, and in particular, we use the local linear regression.<sup>14</sup>

Following Bajari and Kahn (2005), we consider a linear approximation of  $\mathbf{p}_t(X_j, \xi_j)$  in a local neighborhood of house  $j^*$ 's observed characteristics. Specifically, we consider

$$\log(\mathbf{p}_t(X_j, \xi_j)) = \alpha_{j^*,0} + \sum_{k=1}^m \alpha_{j^*,k} x_{j,k} + \xi_j, \quad (16)$$

where  $\alpha_{j^*} = (\alpha_{j^*,0}, \dots, \alpha_{j^*,m})$  is a vector of the hedonic coefficients that represent the implicit prices faced by buyer  $i$  who has chosen house  $j^*$ , and we use a logarithm of the price function instead of its level in order to improve the fitting of the price function. In (16), we locally fit the price function in a neighborhood of the observed characteristics  $X_{j^*}$ , but not in a neighborhood of  $\xi_{j^*}$ , because local fitting around  $\xi_{j^*}$  is not feasible, given that we do not observe  $\xi_{j^*}$ .

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<sup>14</sup>Fan and Gijbels (1996) provide detailed treatment on local linear (or polynomial) regression. We could instead use other nonparametric methods such as a kernel estimator (e.g. Nadaraya-Watson estimator or Gasser-Mieller estimator) or a series estimator. However, Bajari and Benkard (2005) found that a local linear kernel estimator as in Fan and Gijbels (1996) worked best. For this reason, we also use the local linear regression.

The equation in (16) implies that once we estimate  $\alpha_{j^*}$ , we may be able to recover an estimate of  $\xi_{j^*}$ . In fact, Bajari and Benkard (2005) and Bajari and Kahn (2005) suggest that we recover an estimate of  $\xi_{j^*}$  by plugging  $(X_{j^*}, \xi_{j^*})$  into (16), which yields

$$\xi_{j^*} = \log(p_{j^*}) - \alpha_{j^*,0} - \sum_{k=1}^m \alpha_{j^*,k} x_{j^*,k}.$$

We estimate  $\alpha_{j^*}$  for each value of  $j = 1, \dots, J_t$  by using local fitting methods. Specifically, we estimate  $\alpha_{j^*}$  by solving

$$\min_{\alpha} \sum_{j=1}^{J_t} \left\{ \log(p_j) - \alpha_0 - \sum_{k=1}^m \alpha_k x_{j,k} \right\}^2 K_B(X_j - X_{j^*}), \quad (17)$$

where  $K_B(\mathbf{v})$  is the kernel function. Given  $K_B(X_j - X_{j^*})$ ,  $\alpha_{j^*}$  can be estimated by weighted least squares for each  $j^*$ . As for  $K_B(\mathbf{v})$ , we use the product of univariate Gaussian kernel, following Bajari and Kahn (2005) who used  $K_B(\mathbf{v}) = \prod_{k=1}^m \frac{1}{b} N(\frac{1}{b} \frac{v_k}{\hat{\sigma}_k})$ , where  $b$  is a scalar bandwidth,  $N(\cdot)$  is the univariate Gaussian kernel, and  $\hat{\sigma}_k$  is the sample standard deviation of  $v_k$ . Instead of Gaussian kernel, we could also use other univariate kernel functions (e.g. Epanechnikov, biweight, etc.). Alternatively, we may also use  $m$ -variate kernel function  $K_B(\mathbf{v}) = \frac{1}{|B|} K(B^{-1}\mathbf{v})$ , where  $B$  is a nonsingular  $m \times m$  matrix for bandwidth,  $|B|$  denotes its determinant, and the multivariate kernel function is given by  $K(\mathbf{v}) = G\{(\sum_{k=1}^m v_k^2)^{1/2}\}$ , where  $G(\cdot)$  is a univariate kernel function.

### 6.2.2 Step 2: applying the first-order condition and estimating $V^1(\beta_i)$ and $V^0(\beta_i)$

Once we estimate  $\hat{\alpha}_{j^*}$  for all  $j = 1, \dots, J_t$ , we use (12) to recover  $\beta_{i,k}$  as follows.

$$\hat{\beta}_{i,k} = \frac{\partial \mathbf{p}_t(X_{j^*}, \xi_{j^*})}{\partial x_{j,k}} = \frac{\partial \log(\mathbf{p}_t(X_{j^*}, \xi_{j^*}))}{\partial x_{j,k}} \times p_{j^*} = \hat{\alpha}_{j^*,k} \times p_{j^*}, \quad \forall k = 1, \dots, m.$$

To recover  $\beta_{i,0}$ , the coefficient on  $\xi_j$  in (11), we use a similar equation as (12). Since  $\frac{\partial \log(\mathbf{p}_t(X_{j^*}, \xi_{j^*}))}{\partial \xi_j} = 1$  in (16), we can easily recover  $\beta_{i,0}$  by  $\hat{\beta}_{i,0} = \frac{\partial \mathbf{p}_t(X_{j^*}, \xi_{j^*})}{\partial \xi_j} = \frac{\partial \log(\mathbf{p}_t(X_{j^*}, \xi_{j^*}))}{\partial x_{j,k}} \times p_{j^*} = p_{j^*}$ .

As for  $V^1(\beta_i)$  and  $V^0(\beta_i)$ , recall that  $V^1(\beta_i) = d_{j^*} \times U_{j^*}(\beta_i) + (1 - d_{j^*}) \times E[U_s(\beta_i) | d_s = 1]$ , and  $V^0(\beta_i) = (1 - d_{j^*}) \times U_{j^*}(\beta_i) + d_{j^*} \times E[U_s(\beta_i) | d_s = 0]$ , where  $U_j(\beta_i) = \sum_{k=1}^m \beta_{i,k} x_{j,k} + \beta_{i,0} \xi_j - p_j$ . Hence, once we recover  $\hat{\beta}_i$  and  $\hat{\xi}_i$ , we can immediately compute  $U_{j^*}(\hat{\beta}_i)$ , so that we can obtain  $V^1(\hat{\beta}_i)$  for buyer  $i$  with  $d_{j^*} = 1$  and  $V^0(\hat{\beta}_i)$  for buyer  $i$  with  $d_{j^*} = 0$ . To estimate  $V^0(\hat{\beta}_i)$  for buyer

$i$  with  $d_{j^*} = 1$  and  $V^1(\hat{\beta}_i)$  for buyer  $i$  with  $d_{j^*} = 0$ , we need to compute the weighted mean of  $U_s(\beta_i)$  by putting more weights on houses with similar characteristics as house  $j^*$ , while putting less weights on houses with different characteristics. For this reason, we use a local linear matching method<sup>15</sup> to estimate  $E[U_s(\beta_i)|d_s = 0]$  for buyer  $i$  with  $d_{j^*} = 1$  and  $E[U_s(\beta_i)|d_s = 1]$  for buyer  $i$  with  $d_{j^*} = 0$ . Specifically, the local linear weighted mean is given by the intercept  $\mu_0$  in the minimization problem

$$\min_{\mu_0, \mu_1} \sum_{s \in D_t^{1-d_{j^*}}} \{U_s(\beta_i) - \mu_0 - (X_s - X_{j^*})' \mu_1\}^2 K_B(X_s - X_{j^*}),$$

where  $D_t^1$  (or  $D_t^0$ ) denotes a set of houses sold through in-house transactions (or cross-house transactions), so that if  $d_{j^*} = 1$ , we compute the local linear weighted mean by using houses in  $D_t^{1-d_{j^*}} = D_t^0$ .

### 6.2.3 Step 3: estimating the distribution of $\gamma_i$ and $c_i$

Once we recover  $V^1(\beta_i)$  and  $V^0(\beta_i)$ , we can easily determine in-house transactions due to efficient matching, since they are in-house transactions such that  $V^1(\beta_i) > V^0(\beta_i)$ . Thus, the fraction of in-house transactions with  $V^1(\beta_i) \geq V^0(\beta_i)$  provides the magnitude of in-house transactions due to efficient matching. As a result, the fraction of the remaining in-house transactions with  $V^1(\beta_i) \geq V^0(\beta_i)$  provides the upper bound on the magnitude of strategic promotion in explaining in-house transactions. This upper bound provides useful information, but to obtain more information on the extent of strategic promotion, we need to estimate the distribution of  $\gamma_i$  and  $c_i$ .

To this end, we use the inequality in (15) and impose a parametric assumption on the distribution of  $\delta_i = \gamma_i + c_i$ . Hence, we do not attempt to fully separate  $c_i$  from  $\gamma_i$ , because that would require stronger assumptions. We instead focus on the marginal effect of strategic promotion by using exclusion restrictions and a natural experiment from a policy change. This approach is still useful because we can also provide welfare measures related to the policy change.

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<sup>15</sup>See, e.g., Heckman, et al. (1997, 1998) and Hong (2013) for more details on a local linear matching method.

Let us begin by considering the following specifications for  $\gamma_i$  and  $c_i$ :

$$\begin{aligned}\gamma_i &= \gamma_0 + W_{1,i}\lambda_1 + W_{2,i}\lambda_2 + \epsilon_i, \\ c_i &= c_0 + Z_i\theta_1 + W_{2,i}\theta_2 + \omega_i,\end{aligned}\tag{18}$$

where  $\gamma_0$  and  $c_0$  are the intercepts,  $\epsilon_i$  and  $\omega_i$  are the error terms, and  $W_i$  is a vector of variables related to transaction costs, but  $W_{1,i}$  is only related to transaction costs, while  $W_{2,i}$  is related to both transaction costs and strategic promotion. In (18),  $Z_i$  is a vector of variables related to strategic promotion but not related to transaction costs. Though we use excluded variables  $Z_i$  that only affect strategic promotion, we cannot separately identify  $\gamma_i$  and  $c_i$ , because we cannot distinguish  $\gamma_0$  from  $c_0$  without further restrictions, and  $W_{2,i}$  enters both  $\gamma_i$  and  $c_i$ .

Therefore, our main approach for the step 3 considers  $\delta_i = \gamma_i + c_i$  as follows:

$$\delta_i = \delta_0 + Z_i\theta_1 + W_{1,i}\delta_1 + W_{2,i}\delta_2 + \eta_i,\tag{19}$$

where  $\delta_0 = \gamma_0 + c_0$ ,  $\delta_1 = \lambda_1$ ,  $\delta_2 = \lambda_2 + \theta_2$ , and  $\eta_i = \epsilon_i + \omega_i$ . Hence, as long as we have excluded variables  $Z_i$ , we can identify and estimate the marginal effect of strategic promotion due to changes in  $Z_i$ . To estimate  $\theta_1$ , we use the following probability model based on the inequality in (15):

$$\Pr(d_j = 1) = \Pr [V^1(\beta_i) - V^0(\beta_i) + \delta_0 + Z_i\theta_1 + W_{1,i}\delta_1 + W_{2,i}\delta_2 + \eta_i > 0].\tag{20}$$

If we do not impose any assumption on  $\eta_i$ , we can obtain bounds on  $\theta_1$ . To obtain point identification, we follow Bajari and Kahn (2005) and impose a parametric distribution on  $\eta_i$ . However, the identification of  $\theta_1$  does not rely on a particular parametric assumption for  $\eta_i$ . In our application, we assume a normal distribution, simply because it is straightforward to estimate a probit model.

The probability model in (20) is closely related to the reduced form regression, but its advantage is that we can fully control for efficient matching by including  $V^1 - V^0$  in (20), and also estimate the magnitude of the marginal effect of strategic promotion, relative to  $V^1 - V^0$ . In particular, given that we observe a policy change that reduces incentives for strategic promotion, we can estimate the effect of this policy change on strategic promotion in terms of changes in  $c_i$ .

## 7 Results from Structural Estimates

For our structural estimation, we use data from 2005 and 2007.<sup>16</sup> In the first step, we estimate nonparametric price functions using the local linear regression as described in Section 6.2.1. We include the following variables for  $X_j$ : the number of bedrooms; the number of washrooms; the number of garages;  $\log(\text{lot.front})$  and  $\log(\text{lot.depth})$ , where  $\text{lot.front}$  and  $\text{lot.depth}$  measures the size of a house;  $\text{map.row}$ ,  $\text{map.column}$ , and  $\text{map.row} \times \text{map.column}$ , where  $\text{map.row}$  (or  $\text{map.column}$ ) is the consecutive number that indicates the latitudinal (or longitudinal) location of a house.

There are two remarks about our application in the step 1. First, the geographic location of a house is an important determinant of house characteristics. Ideally, we would include fixed effects for each location, but such an approach is infeasible in nonparametric estimations because of too many parameters to estimate. As an alternative, we include  $\text{map.row}$ ,  $\text{map.column}$ , and their interactions. Note that including these variables in a standard hedonic regression does not make sense, because house prices are not monotonic in these variables. It makes sense in our framework, however, since we estimate the price function for each buyer by locally fitting the price function in a neighborhood of  $X_{j^*}$ , so that the coefficients on these variables vary across different observations.

Second, housing markets are not clearly defined by a specific time period. Even if we separate housing markets based on the month or the year when houses are sold, this separation is arbitrary. It is not plausible that houses sold in, say, January 2005, consist of one unique market that is separated from houses sold in surrounding months, because houses sold in, say, February 2005 were also likely on the market during January 2005. To address this issue, we compute the kernel function  $K_B(X_j - X_{j^*})$  in (17) not only using  $X_j$  but also using the sales date. This approach reflects the notion that a relevant market for a house sold in, say, January 2, 2005 should be more likely to include houses sold in, say, December 30, 2004, but less likely to include houses sold in, say, July 2, 2005. Specifically, we use  $K_B(X_j - X_{j^*}) \times \frac{1}{b} N(\frac{t_j - t_{j^*}}{b})$ , in place of  $K_B(X_j - X_{j^*})$  in (17), where  $b$  is a scalar bandwidth,  $N(\cdot)$  is the Gaussian kernel, and  $t_j$  is the sales date of house  $j$ .

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<sup>16</sup>We are currently estimating nonparametric hedonic price functions for other years, but it is not finished yet. Our next draft will include the results from all years.

After the step 1 estimation, we recover  $\hat{\beta}_i$  and  $U_{j^*}(\hat{\beta}_i)$  for each buyer in the sample.<sup>17</sup> We then estimate  $V^1(\hat{\beta}_i)$  and  $V^0(\hat{\beta}_i)$  for each buyer, using a local linear matching method described in Section 6.2.2. Table 9 presents summary statistics for the estimated  $V^1(\hat{\beta}_i)$  and  $V^0(\hat{\beta}_i)$ . We compute  $V^1 - V^0$  for each observation, and Panel A reports its distribution. In particular, the first row presents its distribution among in-house transactions, which shows that the mean of  $V^1 - V^0$  is 58,514, and  $V^1 - V^0$  tends to be non-negative for in-house transactions. In fact, Panel B shows that the fraction of observations with  $V^1 - V^0 < 0$  is about 0.27, which means that  $V^1 - V^0$  is positive for about 73% of in-house transactions. In other words, about 73% of in-house transactions in our sample are likely to have resulted from efficient matching, in that buyers in these transactions prefer in-house transactions to cross-house transactions in terms of house characteristics. This implies that about 27% of in-house transactions are likely to have resulted from either strategic promotion or low transaction costs. Therefore, the upper bound on the total effect of strategic promotion in explaining in-house transactions is about 27%.

Consequently, we further use the estimated  $V^1 - V^0$ , and estimate the distribution of  $\gamma_i$  and  $c_i$  using the step 3 estimation approach described in Section 6.2.3. Table 10 presents the coefficient estimates from estimating the probability model in (20). We include `low.commission` and `per.transaction.split` in  $Z_i$ , while  $W_i$  contains  $\log(\text{days.on.market})$  and  $\log(\#\text{listings})$ . We also include REBBA indicator variable for the policy change that is likely to have reduced incentives for strategic promotion. Note that this policy was implemented in 2006, and so year 2005 is the period before the policy change, while year 2007 is the period after the policy change. Column 1 includes only this indicator variable, whereas column 2 also includes the interactions between REBBA and `low.commission` as well as `per.transaction.split`.

The estimation results in both columns show that the coefficient estimates on `low.commission` and `per.transaction.split` are both positive and statistically significant, which indicates that  $c_i$  due to

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<sup>17</sup>In the utility function in (11), we enter `#bedrooms`, `#washrooms`, `#garages`,  $\log(\text{lot.front})$ , and  $\log(\text{lot.depth})$  linearly, so that we can recover  $\hat{\beta}_{i,k}$  following the procedure described in Section 6.2.2. However, for `map.row`, `map.column`, and their interaction, we enter the quadratic terms in the utility function in order to reflect the notion that if a buyer purchased a house in, say, `map.row = 20`, she is likely to prefer houses in that location to houses in, say, `map.row = 15` or `map.row = 25`. Specifically, for these location variables, we include  $\beta_{i,k}x_{j,k}^2 + x_{j,k}^2$  in the utility function which can generate the inverted U-shaped utility function with the single parameter. For these variables,  $\hat{\beta}_{i,k}$  can be recovered by  $\hat{\beta}_{i,k} = (\hat{\alpha}_{j^*,k}p_{j^*} - 1)/2x_{j^*,k}$ .

$Z_i\theta_1$  in (18) is positive and significant. These estimates imply the strong presence of the implicit cost of visiting houses listed by other brokerages (i.e. cross-house transactions), thus providing evidence for strategic promotion. In column 2, the coefficient estimates on the interactions with REBBA are both negative. While the interaction with `per.transaction.split` is statistically significant, the interaction with `low.commission` is not estimated precisely. Nevertheless, both estimates imply that REBBA has lowered  $c_i$  due to  $Z_i\theta_1$ , thereby weakening the incentives for strategic promotion.

To quantify the magnitude of the implicit cost  $c_i$  due to  $Z_i\theta_1$ , we further compute  $Z_i\hat{\theta}_1$  for each observation. However, the implicit cost associated with strategic promotion does not matter if a buyer purchased her house through a cross-house transaction, or if a buyer purchased a house that matches her preference best through an in-house transaction ( $V^1 \geq V^0$ ). For this reason, we compute  $Z_i\hat{\theta}_1$  only for the observations from in-house transactions with  $V^0 > V^1$ . To assess the magnitude of the implied  $c_i$  due to  $Z_i\hat{\theta}_1$ , we further compute the percentage of the implied  $c_i$  due to  $Z_i\hat{\theta}_1$ , relative to  $V^0$ . Note that for buyers who have chosen in-house transaction,  $V^0$  is the expected utility (excluding  $c_i$ ) from cross-transaction, had they chosen cross-house transactions. Hence, the computed percentage reflects the loss in their potential utility attributable to strategic promotion.

Panel A of Table 11 reports the average value of these percentages. We calculate the percentages separately for the samples before and after REBBA. Before the REBBA was implemented, buyers' utility loss, measured as a percentage of the extra cost imposed by strategic promotion relative to the maximum utility they could obtain, is 1.68%. When translated into the monetary value, this number is almost comparable to commission income that an agent receives from a completed transaction. The utility loss associated with strategic promotion is reduced to 0.35% after the implementation of the REBBA. We also compute the counterfactual value for the sample before REBBA by setting REBBA equal 1, whereas for the sample after REBBA, we compute the counterfactual value by setting REBBA equal 0. The average values are also reported in Panel A of Table 11, and they are 0.43% and 1.61% respectively for the sample before REBBA and for the sample after REBBA. These results show that the utility loss due to strategic promotion would have decreased on average by 74% ( $= (1.68 - 0.43)/1.68$ ) for the sample before REBBA, had REBBA been implemented at

that time. A similar interpretation of the results is that the utility loss has decreased on average by 79% ( $= (1.68 - 0.35)/1.68$ ) between the periods before and after the implementation of the REBBA.

The reduced implicit cost associated with strategic promotion is also likely to have lowered in-house transactions due to strategic promotion. To investigate its magnitude, we first compute the predicted probabilities of in-house transactions using our samples before and after REBBA. Panel B of Table 11 reports the mean of these probabilities for the period before and after REBBA. It shows that the fraction of in-house transactions has declined from 0.186 to 0.164.<sup>18</sup> We then compute the counterfactual probabilities of in-house transactions in the absence of REBBA. Specifically, we set the coefficients on `rebba×low.commission` and `rebba×per.transaction.split` equal zero, and compute the predicted probabilities of in-house transactions for the samples after REBBA. We find that the mean of these probabilities is 0.173 as reported in Panel C. Hence, in the absence of REBBA, the fraction of in-house transactions would have been 0.173, instead of 0.164. These results indicate that REBBA has weakened the impact of strategic promotion on buyers' home search process, which accounts for 41% of a decrease in in-house transactions before and after REBBA.

## 8 Conclusion

Over 20% of real estate transactions occur within the same brokerage. In this paper, we examine the causes and implications of in-house transactions in the real estate brokerage industry. We find that in-house transactions occur not only for efficiency reasons but also for incentive reasons. Our estimates suggest that over 70% of in-house transactions result from brokerages' ability to specialize in certain areas and to economize on transaction cost, both of which bring buyers and sellers together in an efficient manner. On the other hand, the remaining in-house transactions are caused by agents' financial incentives to steer their buyer clients toward internal listings. The impact of agents' promotion on in-house transactions is stronger when buyers have higher search cost and when cooperating agents receive less compensation from listing agents. The results are

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<sup>18</sup>Note that the means of the predicted probabilities are almost the same as the actual fraction of in-house transactions among our samples.

robust even after we control for efficient matching due to brokerage specialization and transaction efficiencies. These findings are consistent with an agent-intermediated search model where house search is costly and agents possess superior information about the housing market.

Overall, our results are in line with previous work that highlights the conflict of interest and misaligned incentives in the real estate brokerage industry. While existing work on in-house transactions has almost exclusively focused on how dual agency affects time on the market and house price, our work examines the underlying drivers of in-house transactions and studies how dual agency affects home allocation process and quality of the match. In terms of welfare consequence, we find that agents' strategic promotion reduces the utility of home buyers by 1.68% before the implementation of the REBBA and by 0.35% afterwards.

Our findings are particularly relevant in the current housing markets as every state in the U.S. has now required agency disclosure, indicating a regulatory reliance on disclosure to reduce inefficiency resulted from in-house sales. Our results suggest that the legislation does have some desired effects by helping homebuyers make more informed choices and by constraining agents' ability to strategically promote. However, it cannot completely eliminate information inefficiencies and hence utility loss, possibly due to the difficulty of monitoring and enforcing the required disclosure.

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Figure 1: Cooperating Brokerage's Fraction of In-House Transactions at District-level

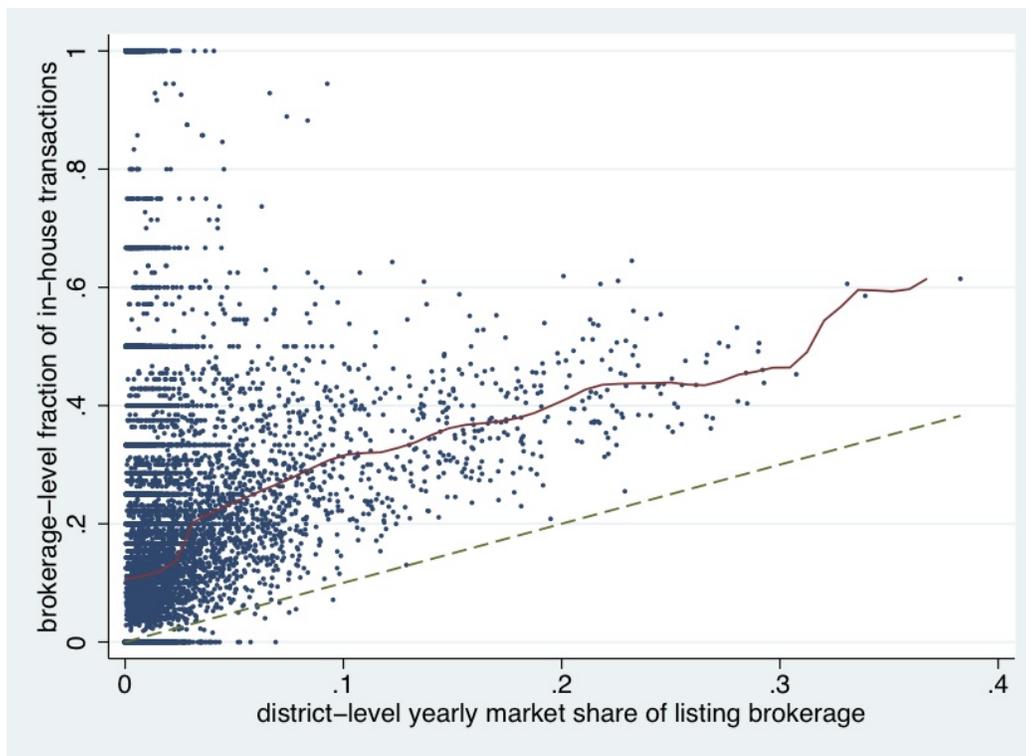


Table 1: Fraction of In-House Transactions by Franchises<sup>a</sup>

	brokerage in-house	franchise in-house	total share
Re/Max	0.223	0.458	0.309
Homelife	0.131	0.255	0.135
Royal LePage	0.220	0.304	0.129
Sutton Group	0.166	0.241	0.114
Century21	0.140	0.205	0.086
Coldwell Banker	0.121	0.142	0.038
Prudential	0.253	0.281	0.029
MinCom	0.293	0.328	0.007
Exit Realty	0.133	0.135	0.006
Keller Williams	0.135	0.141	0.005
Realty Executives	0.142	0.145	0.003
Independent	0.154	0.154	0.138
All	0.183	0.299	1.000

<sup>a</sup>For each franchise, we combine all transactions carried out by its franchisees, and the table reports the fraction of brokerage in-house transactions (i.e. cooperating brokerage and listing brokerage are the same), and the fraction of franchise in-house transactions (i.e. cooperating brokerage and listing brokerage belong to the same franchise) for each franchise. “Independent” includes brokerages that are not associated with franchises. Each franchise’s “total share” refers to the share of its transactions among all transactions in our data.

Table 2: Fraction of In-House Transactions by Brokerage Ranking<sup>a</sup>

	brokerage in-house	franchise in-house	total share
ranking.1-10	0.220	0.389	0.214
ranking.11-50	0.195	0.307	0.333
ranking.51-100	0.161	0.282	0.182
ranking.101-200	0.166	0.257	0.150
ranking.201-	0.142	0.199	0.121
All	0.183	0.299	1.000

<sup>a</sup>We rank cooperating brokerages in order of their total market shares in our data. We then group them by their rankings. The table reports the fraction of brokerage in-house transactions (i.e. cooperating brokerage and listing brokerage are the same), and the fraction of franchise in-house transactions (i.e. cooperating brokerage and listing brokerage belong to the same franchise) for each group. Each group’s “total share” refers to the share of its transactions among all transactions in our data.

Table 3: Fraction of In-House Transactions by # Agents<sup>a</sup>

	brokerage in-house	franchise in-house	total share
#agent.501-	0.220	0.331	0.093
#agent.201-500	0.182	0.310	0.242
#agent.101-200	0.177	0.315	0.235
#agent.51-100	0.180	0.308	0.151
#agent.11-50	0.189	0.292	0.126
#agent.1-10	0.161	0.206	0.053
#agent.unknown	0.173	0.250	0.100
All	0.183	0.299	1.000

<sup>a</sup>We collect information on the number of agents for each brokerage, and group brokerages by the number of agents. The table reports the fraction of brokerage in-house transactions (i.e. cooperating brokerage and listing brokerage are the same), and the fraction of franchise in-house transactions (i.e. cooperating brokerage and listing brokerage belong to the same franchise) for each group. Each group’s “total share” refers to the share of its transactions among all transactions in our data.

Table 4: Fraction of In-House Transactions by # Offices<sup>a</sup>

	brokerage in-house	franchise in-house	total share
#office.11-	0.221	0.295	0.082
#office.4-10	0.190	0.330	0.252
#office.2-3	0.195	0.338	0.213
#office.1	0.163	0.265	0.273
#office.unknown	0.172	0.262	0.181
All	0.183	0.299	1.000

<sup>a</sup>We collect information on the number of offices for each brokerage, and group brokerages by the number of offices. The table reports the fraction of brokerage in-house transactions (i.e. cooperating brokerage and listing brokerage are the same), and the fraction of franchise in-house transactions (i.e. cooperating brokerage and listing brokerage belong to the same franchise) for each group. Each group’s “total share” refers to the share of its transactions among all transactions in our data.

Table 5: Fraction of In-House Transactions by Year<sup>a</sup>

	brokerage in-house	franchise in-house	total share
2001	0.202	0.308	0.099
2002	0.189	0.298	0.115
2003	0.189	0.300	0.113
2004	0.186	0.303	0.119
2005	0.192	0.314	0.117
2006	0.193	0.315	0.110
2007	0.177	0.298	0.123
2008	0.169	0.291	0.093
2009	0.153	0.271	0.111
All	0.183	0.299	1.000

<sup>a</sup>The table reports the fraction of brokerage in-house transactions (i.e. cooperating brokerage and listing brokerage are the same), and the fraction of franchise in-house transactions (i.e. cooperating brokerage and listing brokerage belong to the same franchise) for each year based on the date when a house was sold. Each year's "total share" refers to the share of its transactions among all transactions in our data.

Table 6: Baseline Results for In-house Transactions<sup>a</sup>

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
low.commission	0.111** (0.009)	0.111** (0.009)	0.121** (0.020)	0.121** (0.020)	0.101** (0.010)	0.101** (0.010)	0.098** (0.010)	0.098** (0.010)
per.transaction.split	0.010** (0.002)	0.010** (0.002)	-0.001 (0.004)	-0.001 (0.004)				
#listings (in 100)	0.084** (0.001)	0.084** (0.001)	0.071** (0.002)	0.071** (0.002)	0.107** (0.002)	0.107** (0.002)	0.094** (0.002)	0.094** (0.002)
house characteristic	yes							
listing price	yes							
taxes	no	yes	no	yes	no	yes	no	yes
year×month	yes							
district	yes							
house fixed effects	no	no	yes	yes	no	no	no	no
brokerage×region	no	no	no	no	yes	yes	no	no
brokerage×price range	no	no	no	no	no	no	yes	yes
$\bar{R}^2$	0.067	0.067	0.084	0.084	0.087	0.087	0.088	0.088
observations	190594	190594	79518	79518	190594	190594	190594	190594

<sup>a</sup>The dependent variable is the indicator variable for whether the transaction is in-house or not. House characteristics include  $\ln(\text{lot.front})$ ,  $\ln(\text{lot.depth})$ , dummy variables for #bedrooms, #washrooms, #garages, and types of occupants. #listings is the district-level yearly number of listings by the same brokerage as the buyer's cooperating brokerage. For listing price and taxes, we use the logarithm of these variables. The specification with taxes also includes dummy variables for years when properties were assessed for property taxes. Standard errors are in parentheses. \* denotes significance at a 5% level, and \*\* denotes significance at a 1% level.

Table 7: Results for Strategic In-house Transactions<sup>a</sup>

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
no.subway×low.commission	0.114** (0.024)	0.114** (0.024)	0.201** (0.050)	0.200** (0.050)	0.110** (0.024)	0.109** (0.024)	0.114** (0.024)	0.113** (0.024)
no.subway×per.transaction.split	0.022** (0.005)	0.022** (0.005)	0.037** (0.011)	0.037** (0.011)	0.014* (0.006)	0.014* (0.006)	0.002 (0.011)	0.002 (0.011)
low.commission	0.018 (0.022)	0.018 (0.022)	-0.042 (0.045)	-0.040 (0.045)	0.012 (0.022)	0.012 (0.022)	0.006 (0.022)	0.007 (0.022)
per.transaction.split	-0.009* (0.005)	-0.009* (0.005)	-0.033** (0.010)	-0.033** (0.010)				
no.subway	-0.094** (0.007)	-0.093** (0.007)	-0.127 (0.185)	-0.127 (0.185)	-0.102** (0.008)	-0.100** (0.008)	-0.035** (0.008)	-0.034** (0.008)
#listings (in 100)	0.085** (0.001)	0.085** (0.001)	0.071** (0.002)	0.071** (0.002)	0.107** (0.002)	0.107** (0.002)	0.094** (0.002)	0.094** (0.002)
house characteristic	yes							
listing price	yes							
taxes	no	yes	no	yes	no	yes	no	yes
year×month	yes							
district	yes							
house fixed effects	no	no	yes	yes	no	no	no	no
brokerage×region	no	no	no	no	yes	yes	no	no
brokerage×price range	no	no	no	no	no	no	yes	yes
$\bar{R}^2$	0.067	0.067	0.084	0.084	0.087	0.087	0.088	0.088
observations	190594	190594	79518	79518	190594	190594	190594	190594

<sup>a</sup>The dependent variable is the indicator variable for whether the transaction is in-house. House characteristics include  $\ln(\text{lot.front})$ ,  $\ln(\text{lot.depth})$ , dummy variables for #bedrooms, #washrooms, #garages, and types of occupants. #listings is the district-level yearly number of listings by the same brokerage as the buyer's cooperating brokerage. For listing price and taxes, we use the logarithm of these variables. The specification with taxes also includes dummy variables for years when properties were assessed for property taxes. Standard errors are in parentheses. \* denotes significance at a 5% level, and \*\* denotes significance at a 1% level.

Table 8: Results for “Difference-in-differences” using REBBA<sup>a</sup>

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
rebba × no.subway × low.commission	-0.060 (0.050)	-0.061 (0.050)	0.020 (0.108)	0.020 (0.108)	-0.101** (0.051)	-0.101** (0.051)	-0.093** (0.046)	-0.094** (0.046)
rebba × no.subway × per.transaction.split	0.006 (0.007)	0.007 (0.007)	0.008 (0.015)	0.008 (0.015)	0.012 (0.007)	0.013 (0.007)	0.012 (0.008)	0.012 (0.008)
rebba × #listings (in 100)	0.008*** (0.002)	0.008*** (0.002)	0.012*** (0.004)	0.012*** (0.004)	0.006*** (0.002)	0.006*** (0.002)	0.006*** (0.002)	0.006*** (0.002)
no.subway × low.commission	0.132** (0.030)	0.132** (0.030)	0.185** (0.059)	0.184** (0.059)	0.141** (0.030)	0.141** (0.030)	0.143** (0.030)	0.143** (0.030)
no.subway × per.transaction.split	0.021** (0.006)	0.020** (0.006)	0.035** (0.013)	0.035** (0.013)	0.010 (0.007)	0.009 (0.006)	-0.002 (0.011)	-0.002 (0.011)
#listings (in 100)	0.082** (0.001)	0.082** (0.001)	0.071** (0.002)	0.071** (0.002)	0.093** (0.003)	0.093** (0.003)	0.105** (0.002)	0.105** (0.002)
rebba × low.commission	0.121** (0.045)	0.122** (0.045)	0.076 (0.099)	0.077 (0.099)	0.155** (0.046)	0.156** (0.046)	0.149** (0.046)	0.150** (0.046)
rebba × per.transaction.split	-0.012 (0.007)	-0.012 (0.007)	-0.017 (0.015)	-0.018 (0.015)	-0.013 (0.007)	-0.013 (0.007)	-0.011 (0.007)	-0.012 (0.007)
low.commission	-0.023 (0.026)	-0.023 (0.026)	-0.063 (0.052)	-0.063 (0.052)	-0.040 (0.027)	-0.040 (0.027)	-0.044 (0.027)	-0.044 (0.027)
per.transaction.split	-0.004 (0.005)	-0.004 (0.005)	-0.026* (0.012)	-0.025* (0.012)				
no.subway	-0.094** (0.007)	-0.093** (0.007)	-0.125 (0.185)	-0.125 (0.185)	-0.102** (0.008)	-0.100** (0.008)	-0.035** (0.008)	-0.034** (0.008)
rebba	-0.070** (0.017)	-0.019 (0.025)	-0.136** (0.034)	-0.092 (0.054)	-0.057** (0.017)	0.002 (0.026)	-0.055** (0.017)	-0.000 (0.025)
house characteristic	yes							
listing price	yes							
taxes	no	yes	no	yes	no	yes	no	yes
year × month	yes							
district	yes							
house fixed effects	no	no	yes	yes	no	no	no	no
brokerage × region	no	no	no	no	yes	yes	no	no
brokerage × price range	no	no	no	no	no	no	yes	yes
$R^2$	0.067	0.067	0.084	0.084	0.087	0.087	0.088	0.088
observations	190594	190594	79518	79518	190594	190594	190594	190594

<sup>a</sup>The dependent variable is the indicator variable for whether the transaction is in-house. House characteristics include ln(lot.front), ln(lot.depth), dummy variables for #bedrooms, #washrooms, #garages, and types of occupants. #listings is the district-level yearly number of listings by the same brokerage as the buyer’s cooperating brokerage. For listing price and taxes, we use the logarithm of these variables. The specification with taxes also includes dummy variables for years when properties were assessed for property taxes. Standard errors are in parentheses. \* denotes significance at a 5% level, and \*\* denotes significance at a 1% level.

Table 9: Summary Statistics for  $V^1$  and  $V^0$  from Step 2 Estimation<sup>a</sup>

A. distribution of $V^1 - V^0$				
	mean	10th	median	90th
among in-house transactions	58,514	- 27,922	30,463	136,414
among cross-house transactions	-46,366	-115,972	-31,107	33,789
among all transactions	-27,350	-106,735	-21,078	57,704
B. fraction of observations with $V^1 < V^0$ among in-house transactions				
in 2005	0.276			
in 2007	0.264			
in 2005 and 2007	0.271			

<sup>a</sup>The table reports descriptive statistics for  $V^1(\beta_i)$  and  $V^0(\beta_i)$  estimated from the step 2 estimation described in Section 6.2.2. We use data from 2005 and 2007.

Table 10: Step 3 Probit Estimation Results<sup>a</sup>

	(1)	(2)
low.commission	0.571** (0.067)	0.640** (0.091)
per.transaction.split	0.062** (0.017)	0.103** (0.022)
rebba × low.commission		-0.144 (0.134)
rebba × per.transaction.split		-0.088** (0.032)
rebba	-0.063** (0.016)	-0.025 (0.021)
log(days.on.market)	0.032** (0.008)	0.032** (0.008)
log(#listings)	0.195** (0.005)	0.195** (0.005)
$V^1 - V^0$ (in 100,000)	1.010** (0.014)	1.010** (0.014)
constant	-1.651** (0.034)	-1.668** (0.034)
observations	42627	42627

<sup>a</sup>The dependent variable is the indicator variable for whether the transaction is in-house or not. We use data from 2005 and 2007. Standard errors are in parentheses. \* denotes significance at a 5% level, and \*\* denotes significance at a 1% level.

Table 11: Implied Results from Step 3 Estimates<sup>a</sup>

A. average implied $c_i$ due to low.commission and per.transaction.split as % relative to $V^0$ (only for in-house transactions with $V^0 > V^1$ )	
for the sample before REBBA	
actual (without REBBA)	1.68%
counterfactual (if REBBA were implemented)	0.43%
for the sample after REBBA	
actual (with REBBA)	0.35%
counterfactual (if REBBA were not implemented)	1.61%
B. predicted mean probability of in-house transactions	
before REBBA	0.186
after REBBA	0.164
C. counterfactual mean probability of in-house transactions in the absence of REBBA	
for the sample after REBBA	0.173
D. % reduction in in-house transactions attributable to REBBA reducing strategic promotion	
= $(0.173-0.164)/(0.186-0.164) \times 100\% = 41\%$	

<sup>a</sup>In Panel A, the implied  $c_i$  due to low.commission and per.transaction.split is  $Z_i \hat{\theta}_1$ . We compute the percentage of  $Z_i \hat{\theta}_1$  relative to  $V^0$  for in-house transactions with  $V^0 > V^1$ . The table reports the average value of the computed percentages. The counterfactual result for the sample before REBBA is computed by setting REBBA equal 1 for this sample, whereas that for the sample after REBBA is computed by setting REBBA equal 0. In Panel C, to compute the counterfactual mean probability of in-house transactions without REBBA, we use only the samples after REBBA and compute the predicted probability of in-house transactions by setting the coefficients on  $rebba \times low.commission$  and  $rebba \times per.transaction.split$  equal zero. The table reports the mean of these probabilities.