Conflicts of Interest and Agent Heterogeneity in Buyer Brokerage

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Abstract

This paper investigates the incentives of agents working with buyers (buying agents) under the fixed percentage commission system (FPCS) and the implications on housing market outcomes. Our model shows that the FPCS without a binding contract between the buyer and the buying agent could produce outcomes that are more equitable for buyers. The reason is that the absence of a binding contract helps mitigate the conflict of interest between the buyer with her agent and ensures a better alignment of interest between them. Our model shows that agent heterogeneity plays an important role in determining the binding force of the FPCS in the absence of a binding contract. Results from simulations and empirical analyses using house transactions in Canada support our model predictions.

Keywords: Real estate; Housing; Conflict of interests; Buyer brokerage; Non-binding principal-agent relationships.

JEL: D82 (Asymmetric and Private Information • Mechanism Design); L85 (Real Estate Services); R21 (Housing Demand); R31 (Housing Supply and Markets).

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1. Introduction

Although a contract between the buyer and the buyer's agent (the "buying agent") is not mandatory in the housing market, the buying agent still has fiduciary duties to the buyer, creating a principal-agent relationship between the buyer and the buying agent.[1] In a recent lawsuit filed by the Department of Justice (DOJ), the National Association of Realtors (NAR) was accused of allegedly violating four categories of antitrust laws.[2] Among the four anticompetitive practices, three were about the buying agent.

Most of the existing literature focuses on seller brokerage because the principal-agent relationship between the seller and the seller's agent are clearly specified in a mandatory binding contract.[3] However, relative to the extensive literature on seller brokerage,[4] limited studies focus on buyer brokerage, except, for example, Yavas and Colwell (1999), Sahin, Sirmans, and Yavas (2013), and Hayunga and Munneke (2019).

This paper focuses on buyer brokerage under the fixed percentage commission system (FPCS). Under the FPCS which is widely used in most markets in North America, the seller pays her agent a predetermined percentage of the final sale price (see Han and Strange, 2015, for a survey). The commission is then split between the seller's agent (also called the listing agent) and the buyer's agent. Among the four participants (buyer, seller, listing agent, and buying agent) under the FPCS, the buyer is the only one who benefits from a low sale price. As a result, the FPCS can result in a misalignment of interest between the buyer and the buying agent.

We investigate buying agents' incentive problems and their implications on transaction outcomes.

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1 For example, for our sample of house sales in the province of Quebec, Canada, a real estate license holder not bound by a brokerage contract represents the party who has requested the holder act as an intermediary and must protect and promote the interests of the party represented (Real Estate Brokerage Act, Chapter C-73.2, r.1 s.14 & s.15). More examples and details are provided in the Online Supplementary Appendix 1 (OSA 1).

2 "According to the complaint, NAR's anticompetitive rules, policies, and practices include: (i) prohibiting MLSs that are affiliated with NAR from disclosing to prospective buyers the commission that the buyer broker will earn; (ii) allowing buyer brokers to misrepresent to buyers that a buyer broker's services are free; (iii) enabling buyer brokers to filter MLS listings based on the level of buyer broker commissions offered; and (iv) limiting access to the lockboxes that provide licensed brokers with access to homes for sale to brokers who work for a NAR-affiliated MLS." https://www.justice.gov/opa/pr/justice-department-files-antitrust-case-and-simultaneous-settlement-requiring-national (Accessed February 20, 2021).

3 For example, the exclusive right-to-sell listing agreement.

4 To illustrate, Rutherford et al. (2005), Levitt and Syverson (2008), and Allen et al. (2015) find that agent-owned houses are sold at a premium compared to non-agent-owned houses while having similar listing times.

We start with a model to replicate the negotiation process between sellers and buyers, where a buyer considers the buying agent's advice on a proposed offer with no binding contract. Therefore, a potential buyer can work with different buying agents. If the buyer detects an agent's self-interest behavior, the buying agent receives nothing if the buyer walks away. Thus, the absence of a binding contract creates a constraint for buying agents (subsequently referred to as the "no-contract constraint") which can help induce lower sale prices that benefit the buyer.

There are two reasons for our focus on the negotiation stage. First, the growth of Fintech platforms such as Realtor, Trulia, and Zillow diminish a buying agent's role in the searching and matching stage (particularly information provision) by providing buyers free access to listings with sufficient property information. Thus, the negotiation stage becomes relatively more important in the home buying process.[5] Second and more importantly, agent heterogeneity affects the extent of (mis)alignment of the buying agent with the buyer's interest and ultimately the housing outcome primarily when the buying agent suggests an offer price to the buyer in the negotiation process.

Our model shows that buying agents without a binding contract are less likely to be self-interested and to misguide home buyers from suggesting a higher offer. Our model also suggests that the FPCS can produce offer prices that are more equitable for the buyer. The reason is that the no-contract constraint imposes the cost of losing clients due to the buying agent's self-interest behavior, hence increasing the buying agent's incentive to behave in the best interest of the buyer.

Our model also introduces an important role of agent heterogeneity in determining the binding force of the no-contract constraint. We categorize buying agents into two types, high *versus* low, and define high-type agents as those with better skills in predicting both buyers' and sellers' reservation prices and with stronger impacts on the decisions of home buyers. We show that the binding force of the no-contract constraint is lessened for high-type buying agents, resulting in less favorable housing market outcomes for buyers.

We next conduct simulations to examine our model predictions by using parameters generated from a large dataset of house transactions in the province of Quebec, Canada. Our simulation studies show that the no-contract constraint moderates the conflict of interest between buying agents and home buyers. More importantly, the binding force of the no-contract constraint is lessened for high-type buying agents.

[5] For example, Williams (2018) focuses on buyers' search. In his model, the buyer's agent plays a rather limited role.

Our simulation results further suggest that the information asymmetry level and the commission rate splits to buying agents also impact the effect of the no-contract constraint on the efficacy of the FPCS in buyer brokerage.

Lastly, we conduct empirical analyses to examine the extent to which different types of agents are bound by the no-contract constraint under FPCS. Our empirical results suggest that buyers who use the assistance from high-type buying agents end up with less favorable outcomes. Given the important role of asking price in negotiation (Han and Strange, 2016), our outcome variable is measured by the ratio of the final sale price to the last asking price. We examine various binding forces. Given information asymmetry, buyers who use high-type buying agents face more unfavorable outcomes in transactions of atypical houses, first-time listed houses, old-age houses, and high-value houses. We also find that buyers who use high-type buying agents end up with more unfavorable outcomes when the buying agents are receiving a higher commission split and when there are high collusion possibilities between the buying agent and the listing agent. Also, we find that buyers using high-type agents end up with less unfavorable outcomes when buying agents receive a fixed amount commission.

Our study makes several contributions to the literature. To the best of our knowledge, we are the first to examine the role of agent heterogeneity in incentive problems and pricing implications in buyer brokerage. Within this context, we investigate the efficiency of the FPCS through theoretical models, simulations, and empirical analyses. For theoretical studies, the most closely related studies to ours are Williams (1998) and Fisher and Yavas (2010) who study the FPCS with respect to the agent's search effort level, search intensity, assuming a constant negotiating price. Our model differs from these studies in that we focus on the negotiation process. Specifically, we model a buying agent's behavior on the proposed offer price while assuming a constant search time for a house. Furthermore, our model extends Yavas and Colwell (1999) who propose a more efficient but not widely used commission system.[6] While Yavas and Colwell focus on the time-to-sell dimension of the agency issue assuming that the negotiated price is given, we focus on the price determination during the negotiating stage. We argue that the lack of contracts between buying agents and buyers creates no-contract constraints on the buying agent's self-interest behavior. This constraint can mitigate the misalignment of interest between

[6] Yavas and Colwell (1999) introduce a more efficient commission system where the seller pays the listing agent a fixed percentage of a predetermined fixed amount of commission and the buying agent receives the rest of the predetermined total commission.

the buyer and her agent by imposing a cost of losing clients on the buying agent, and thus enhances the efficacy of the widely-used FPCS.

Recent empirical studies find that agents purchase houses for themselves at a discount compared to houses purchased for their clients (Allen, Rutherford, Rutherford, and Yavas, 2015; Agarwal, He, Sing, and Song, 2019). Our study also empirically contributes to the scant literature in buyer brokerage by examining the heterogeneity of buying agents on final transaction outcomes.

More broadly, our study complements other works that document the behaviors of expert advisors and the agency problems between intermediaries and their clients when agents receive compensations from upstream firms and have directional conflicts of interests with their clients. For example, the literature studying the behavior of mortgage brokers claims agency problems between households and their mortgage brokers who often receive commissions from lenders (Robles-Garcia, 2019). Studies in the insurance industry claim that insurance brokers, acting as expert advisors for clients, receive commissions from insurance companies based on the premiums paid by the insured, distorting insurance brokers' service and creating conflicts of interest between brokers and those insured. Our study suggests that the lack of binding contracts between brokers and clients creates no-contract constraints on broker's behaviors, which may alleviate somewhat the conflict of interest between brokers and their clients.

The remainder of the paper is organized as follows. In Section 2, we review the institutional background of the real estate brokerage system. In Section 3, we model the negotiating stage under the FPCS with and without a written contract between buyers and buying agents. In Section 4, we describe the data used in the simulations and empirical analyses. In Section 5, we conduct simulations to understand the implications of the model. In Section 6 we present and discuss the empirical hypotheses and results. Section 7 concludes the paper.

2. Institutional Background

Real estate agents assist buyers and sellers in searching, matching, and negotiating in most housing transactions. The relationship between sellers and listing agents are bound by an exclusive right-to-sell listing agreement, under which the listing agent earns a sales commission whether the seller, listing agent, or buying agent finds the final buyer. If another cooperative agent, usually called the buying agent or buyer's broker, is involved in the transaction, the sale commission is split between both agents.

In most cases, the sale commission is determined by a fixed percentage of the final sale price and is paid by home sellers. Unlike the relationship between sellers and listing agents, the relationship between buyers and buying agents are not necessarily bound by contracts. For example, in British Columbia, Manitoba, and Quebec in Canada, and California, Indiana, and Texas in the United States, an exclusive contract, also called the buyer's representative agreement (BRA), between buyers and their buying agents is not mandatory.[7]

Under the fixed percentage commission system (FPCS), buyers can engage with as many buying agents as they want if there is no binding contract signed between buyers and buying agents. However, only the first buying agent (or first buying agent group) who shows the buyer the house and assists the buyer in the negotiation gets the split commission. Thus, all else equal, unbinding the relationship between the buyer and the buying agent allows home buyers to walk away, mitigating the misalignment of interests between the buyer and the buying agent.

Home buyers in some regions of North America sign contracts with buying agents that they work with and have fiduciary duties to act in the best interests of the home buyer (e.g., Alberta, Canada, and Illinois). In our study, buying agents in Quebec (named "selling brokers") are legally considered to be representatives of buyers and have fiduciary duties to buyers even in the absence of written contracts.[8] Therefore, the buying agent (or the cooperating agent) is not always characterized as a sub-agent of the listing agent because there is no contract to identify the buying agent's fiduciary duties to the buyer and the buying agent is compensated by home sellers. In contrast, in Florida, both listing agents and buying agents act as only transaction agents and have no liability to both sellers and buyers from achieving the best prices for their clients in the absence of a written contract. However, no matter whether the buying agent bears legal responsibility of acting on behalf of the buyer, buying agents have no liability from not achieving a low final sale price since they get paid by sellers and their compensation is based on the final sale price unless specified otherwise. Thus, the buying agents have financial incentives not to act in the best interests of their home buyer clients (Allen et al., 2015).

3. Model

[7] Online Supplementary Appendix 1 (OSA 1) summarizes the requirements of a BRA and the cost for buyers to walk away from the relationship with their buying agents in some areas in North America as examples.

[8] The situation is similar in Manitoba, Canada, and Texas.

In this section, we construct a simple model to replicate the activities of buyers, sellers, and their agents in a one stage take-it-or-leave-it (TILI) negotiation under the FPCS. In the Online Supplementary Appendix 2 (OSA 2), we extend the model to two-stage and multi-stage TILI negotiations and find qualitatively similar results.[9]

In our model, the buying agent suggests offer prices to maximize her payoffs in the negotiating stage. Our model has two important assumptions. First, compared with the cost of time and pressure from selling a house, the opportunity cost of time spends on searching for a house by the buyer is less valuable under normal market conditions. This is a plausible assumption when comparable houses for sale and rental options are available to the buyer.[10] Thus, our model focuses on the buying agent's suggested offer price assuming that the buyer's searching time is given. Second, compared with the buying agent who visits many properties more than once, buyers have less access to the information about the market for listed houses and particular properties.[11] This is different from the sell side in which the seller knows more about her property but less about the source of potential buyers than her agent, and thus more highly values other professional services such as marketing the property. Therefore, our model focuses on the services of buying agents in suggesting offer prices for buyers in negotiations. Following the literature, we assume that all participants are risk neutral (e.g., Yavas, 1992, and Allen et al., 2015).

Let S and B denote seller and buyer, whose reservation price for house i is R_i^S and R_i^B, respectively.[12] The buyer's reservation price, R_i^B, is the perceived value of the house after visiting it. We assume that each buyer-seller pair only participates in one negotiation simultaneously. Unlike the seller who signs a contract with her listing agent, the buyer can simultaneously deal with multiple buying agents with different types denoted by $Q,\ Q \in \{Q_H, Q_L\},\ Q_H > Q_L$, where subscripts H and L refer to high and low type agent. We define high-type agents as those with better skills in predicting the reservation prices of both buyers and sellers and stronger persuasive impacts on their clients.

[9] In addition, we find a better alignment of interests between the buyer and the buying agent with more negation rounds between the buyer and the seller.

[10] If there are many comparable houses available for sale, the buyer's cost from losing a chance on the property they really would have liked to get is relatively low. Thus, buyers might not be willing to pay a high price to buy fast. In addition, under normal market conditions, buyers are expected to behave rationally so that they are less likely to "over-pay". Our model does not address negotiations in a bidding war market (see Han and Strange, 2014).

[11] Buyers can access information about the market for listed houses through local real estate brochures and online real estate platforms (e.g., Realtor.com and Zillow) but they do not have access to the type of information that a buying agent can obtain inhouse or through their connections. The knowledge gap between a buyer and buying agent for a specific property narrows somewhat as the buyer approaches the formulation and making of a purchase offer.Buyers can access information about the market for listed houses through local real estate brochures and online real estate platforms (e.g., Realtor.com and Zillow).

[12] The reservation price is based on the valuation for the house and the present value of the future cost if the deal is not accepted.

In the negotiating stage, we first assume that the markets for both sellers and buyers are normal and that offers are accepted if they match each party's reservation price. We also assume that there are positive gains from reaching an agreement for any buyer-seller pair, $R_i^B > R_i^S$. In other words, the probability for a successful negotiation is positive to ensure that modeling is meaningful. Lastly, we assume there are no binding contracts between buyers and their buying agents.[13] In this case, if a buying agent suggests an offer price higher than the buyer's reservation price R_i^B plus a tolerance range, denoted by φ_j, that is set by the buyer for the buying agent, the buyer would not accept the suggested price and would cease the relationship with that buying agent. The tolerance range depends on the buying agent's type and $\varphi_j \in \{\varphi_H, \varphi_L\}$ with $\varphi_H > \varphi_L$, so that a high-type buying agent also has stronger impacts on buyers by persuading the buyer to make a higher offer.

The buying agent does not know the buyer and seller's reservation prices, R_i^B and R_i^S, but forms predictions, denoted as $\widehat{R_i^B}$ and $\widehat{R_i^S}$, which follow a log-normal distribution. We assume the median of each log-normal distribution equals the true value of the reservation price R_i^S and R_i^B. Therefore, the probability that an agent's predicted reservation price falls above or below the true reservation price would be the same. The mean (μ) of the variable's natural logarithm is the same for the high and the low type agents, where $\mu^B = ln(R_i^B)$; $\mu^S = ln(R_i^S)$. We also expect the accuracy or the predicting skill for the high-type buying agent for predicting the reservation prices of both sellers and buyers to be greater than that for the low-type buying agent, $\sigma_H^B < \sigma_L^B$ and $\sigma_H^S < \sigma_L^S$ where σ represents the standard deviation of the logarithm of the predicted reservation price.

There are three possible outcomes in the one stage take-it-or-leave-it (TILI) negotiation under our assumptions:

Case 1: If $R_i^B \geq p_i^a$, the buyer accepts the asking price and pays a final sale price of $p_i = p_i^a$. The associated probability is $prob(Case1) = (1 - n)$. **(Outcome 1)**

Case 2: If $R_i^B < p_i^a$, the buyer rejects the asking price and proposes an offer of p_i^c based on the suggestion of the buying agent.

Case 2a: If $R_i^S \leq p_i^c$, the seller accepts p_i^c and receives a final sale price of $p_i = p_i^c$. The associated probability is $prob(Case2a) = n(1 - w)$. **(Outcome 2)**

[13] The buyer can bind with the buying agent contractually and pay the buying agent the commission for searching for a house. In our study, we focus on cases where BRAs are not mandatory because we investigate the effects of the no-contract constraint on the buying agent's behavior.

Case 2b: If $R_i^S > p_i^c$, the seller rejects p_i^c and the negotiation is ended without a deal. The associated probability is $prob(Case2b) = nw$. **(Outcome 3)**

The buying agent risks losing the buyer if she suggests too high of an offer that results in the buyer walking away. If $p_i^c > R_i^B + \varphi_j$, the suggested offer price exceeds the price range set by the buyer, so that the buying agent receives nothing. The associated probability is $prob(lose\ of\ clients) = prob\ (p_i^c > R_i^B + \varphi_j) = v$. The parameters n, w, and v are the probabilities of Case 1, Case 2a, and Case 2b, respectively. Those parameters can be estimated for an actual house transaction.

3.1 One-stage TILI Negotiation with a Binding Contract between the Buyer and the Buying Agent

We first examine the buyer's and the buying agent's payoffs in the negotiation with a binding contract between the buyer and the buying agent. In this case, the buying agent's behavior is not bound by the no-contract ("walk-away") constraint, leaving only the interest misalignment between the buyer and the buying agent.

Buyer's payoff:

$$\pi_B = R_i^B - p_i - kt \tag{1}$$

where k is the unit cost of purchasing a house and t is the cumulative time the buyer spent from initiating the search to negotiating the sale price.[14] Our model assumes that the searching cost (kt) is constant for all buyers and focuses on the proposed offer price.[15] The final sale price of house i, p_i, is:

$$p_i = (1-n)\, p_i^a + n(1-w)\, p_i^c \tag{2}$$

$$\widehat{R_i^S} \le p_i^c \le R_i^B$$

In equation (2), n is the probability of $R_i^B < p_i^a$ and w is the probability of $p_i^c < R_i^S$. w is a decreasing and convex function of p_i^c: $w' < 0$, and $w'' > 0$, indicating that the probability of $p_i^c < R_i^S$ increases with a decrease of p_i^c. The increasing rate is greater when p_i^c gets closer to $\widehat{R_i^S}$, which is the buying agent's predicted value of the seller's reservation price R_i^S.

To illustrate the relationship between the proposed offer price and the predicted reservation price,

[14] The associated unit cost of purchasing a house, k, includes the searching cost, the visiting cost, and opportunity cost such as rents for the current house.
[15] We also extend our model to incorporate the impact of time cost (results unreported). Specifically, we assume heterogenous (or different) time costs (i.e., *kt*) for buyers. We assume that the buyer's time cost has a positive impact on her reservation price (R_i^B) and proposed offer price.

we assume a constant value c which makes $p_i^c = c\widehat{R_i^S}$. Based on equation (2), $1 \le c \le R_i^B/\widehat{R_i^S}$. Then:

$$w = prob(p_i^c < R_i^S) = prob\left(c\widehat{R_i^S} < R_i^S\right) = \Phi\left[\frac{ln(R_i^S) - ln(R_i^S) - lnc}{\sigma^S}\right] = \Phi\left(\frac{-lnc}{\sigma^S}\right) \qquad (3)$$

Replacing p_i in equation (1) by equation (2) and replacing w in equation (2) by equation (3), we get:

$$\pi_B = R_i^B - (1-n)p_i^a - n\left[1 - \Phi\left(\frac{-lnc}{\sigma^S}\right)\right]c\widehat{R_i^S} - kt \qquad (4)$$

$$1 \le c \le \frac{R_i^B}{\widehat{R_i^S}}$$

Then:

$$\frac{\partial \pi_B}{\partial c} = -n\widehat{R_i^S}\left[1 - \Phi\left(\frac{-lnc}{\sigma^S}\right) + \frac{1}{\sigma^S}\phi\left(\frac{-lnc}{\sigma^S}\right)\right] < 0 \qquad (5)$$

From the perspective of the buyer, $c^* = 1$, so that the buyer should propose a low offer price and the optimal offer price should be equal to the predicted reservation price of the seller, $p_i^{c^*} = \widehat{R_i^S}$.

Buying agent's payoff:

$$\pi_{Sa} = \alpha p_i - F \qquad (6)$$

$$\widehat{R_i^S} \le p_i^c \le \widehat{R_i^B}$$

where α is the predetermined fixed commission rate split to the buying agent and F is the total cost associated with the service. $\widehat{R_i^S}$ and $\widehat{R_i^B}$ are the buying agent's predicted value for the seller's reservation price R_i^S and for the buyer's reservation price R_i^B, respectively.

Replacing p_i in equation (6) by equation (2) and replacing w in equation (6) by equation (3), we get:

$$\pi_{Sa} = \alpha\left\{(1-n)p_i^a + n\left[1 - \Phi\left(\frac{-lnc}{\sigma^S}\right)\right]c\widehat{R_i^S}\right\} - F \qquad (7)$$

$$1 \le c \le \frac{\widehat{R_i^B}}{\widehat{R_i^S}}$$

Then:

$$\frac{\partial \pi_{Sa}}{\partial c} = \alpha n\widehat{R_i^S}\left[1 - \Phi\left(\frac{-lnc}{\sigma^S}\right) + \frac{1}{\sigma^S}\phi\left(\frac{-lnc}{\sigma^S}\right)\right] > 0 \qquad (8)$$

From the perspective of the buying agent, $c^{**} = \frac{\widehat{R_i^B}}{\widehat{R_i^S}}$, so that the buying agent would convince the buyer to propose a high offer price and the optimal offer price should be equal to the predicted reservation price of the buyer, $p_i^{c**} = \widehat{R_i^B}$.

In summary, under the FPCS, with a binding contract, a risk neutral buying agent would never suggest an optimal offer price that aligns with the buyer's best interest. If we assume positive gains from the negotiation, $R_i^B > R_i^S$, that are known by all participants, then $\widehat{R_i^B} > \widehat{R_i^S}$ and $p_i^{c**} \neq p_i^{c*}$. The FPCS binds the interest of the buying agent with those of the seller and the listing agent, so that the buyer's interests are not optimized in the housing transaction.

3.2 One-stage TILI Negotiation without a Binding Contract between the Buyer and the Buying Agent

We now examine the buyer's and buying agent's payoffs without a binding contract.

Buyer's payoff:

The buyer's payoff in this case is the same as that in the case with a binding contract because the buyer bears a negligible cost of switching to other buying agents.[16] Under the FPCS without a binding contract, the buyer should propose the lowest possible offer price and the optimal offer price should be equal to the predicted reservation price of the seller, $p_i^{c*} = \widehat{R_i^S}$.

Buying agent's payoff:

$$\pi_{Sa} = \alpha p_i' - F \tag{9}$$

$$p_i' = (1-n)p_i^a + n(1-v)(1-w)p_i^c \tag{10}$$

$$\widehat{R_i^S} \le p_i^c \le \widehat{R_i^B}$$

where v is the probability of losing the buyer (i.e., the buyer leaves for another buying agent). v is an increasing and convex function of p_i^c: $v' > 0$, and $v'' > 0$, indicating that the probability of $p_i^c > R_i^B + \varphi_j$ increases with an increase of p_i^c. The increasing rate is greater when p_i^c gets closer to $\widehat{R_i^B}$.

To illustrate the relationship between the proposed offer price and the predicted reservation price, we assume a constant value h to make $p_i^c = h\widehat{R_i^B}$. Based on equation (2), $\frac{\widehat{R_i^S}}{\widehat{R_i^B}} \le h \le 1$. Since $p_i^c =$

[16] Even when we include the switching cost in the buyer's payoff function, the buyer's optimal offer price stays the same with and without a binding contract because the switching cost is independent of the offer parameter c. Unlike the high switching cost for a seller due to the signed exclusive right-to-sell agreement, switching to another buying agent or buying agent group is less costly for a buyer, especially compared to the cost for the buyer to stay with an unfaithful agent in a competitive brokerage market.

$h\widehat{R_i^B} = c\widehat{R_i^S},\ c = h\frac{\widehat{R_i^B}}{\widehat{R_i^S}}$. Then:

$$v = prob\left(p_i^c > R_i^B + \varphi_j\right) = prob\left(h\widehat{R_i^B} > R_i^B + \varphi_j\right) = \Phi\left[\frac{ln\left(hR_i^B\right) - ln\left(R_i^B + \varphi_j\right)}{\sigma^B}\right] \quad (11)$$

Replacing $p_i{}'$ in equation (9) by equation (10) and replacing v in equation (10) by equation (11), we get:

$$\pi_{sa}{}' = \alpha\left\{(1-n)p_i^a + n\left\{1 - \Phi\left[\frac{ln\left(hR_i^B\right) - ln\left(R_i^B + \varphi_j\right)}{\sigma^B}\right]\right\}\left\{1 - \Phi\left[\frac{-ln\left(h\frac{\widehat{R_i^B}}{\widehat{R_i^S}}\right)}{\sigma^S}\right]\right\}h\widehat{R_i^B}\right\} - F \quad (12)$$

$$\frac{\widehat{R_i^S}}{\widehat{R_i^B}} \le h \le 1$$

To simplify the presentation of the results, we define $X = \frac{-ln\left(h\frac{\widehat{R_i^B}}{\widehat{R_i^S}}\right)}{\sigma^S}$ and $Y = \frac{ln\left(hR_i^B\right) - ln\left(R_i^B+\varphi_j\right)}{\sigma^B}$.

Then:

$$\frac{\partial \pi_{sa}{}'}{\partial h} = \alpha n\widehat{R_i^B}\,[1-\Phi(Y)][1-\Phi(X)] - \frac{\alpha n\widehat{R_i^B}}{\sigma^B}\phi(Y)[1-\Phi(X)] + \frac{\alpha n\widehat{R_i^B}}{\sigma^S}\phi(X)[1-\Phi(Y)] \quad (13)$$

Equation (13) can be positive, negative, or zero, depending on the functions for X and Y, and the standard deviations of predicting the reservation prices for both parties, σ^B and σ^S. When equation (13) is negative, $h^{**} = \frac{\widehat{R_i^S}}{\widehat{R_i^B}}$, and the buying agent should minimize the offer price. The optimal offer price suggested to the buyer should be equal to the predicted reservation price of the seller, $p_i^{c^{**}} = \widehat{R_i^S}$. In this case, $p_i^{c^{**}} = p_i^{c^*} = \widehat{R_i^S}$.

In summary, under the FPCS without a binding contract, a risk neutral buying agent might suggest an optimal offer price that aligns with the buyer's best interests. The buying agent's payoff may be maximized at the optimal offer price of the buyer.

Proposition 1: A no binding contract between the buyer and the buying agent mitigates the misalignment of interest between them and improves the fairness of the fixed percentage commission system (FPCS).

3.3 Binding Force among Different Types of Buying Agents

The predictions resulting from equation (13) depend on the functions of X and Y, and the standard deviations of predicting the reservation prices for both parties, σ^B and σ^S. We assume high-type buying agents have different functions of X and Y, given the value of p_i^c. We identify the probability of losing clients, v, as the cost of being self-interested. We take the first-order partial derivative of equation (11) respect to σ^B and φ_j, respectively, to get:

$$\frac{\partial v}{\partial \sigma^B} = \phi(Y)\frac{\left[ln\left(R_i^B + \varphi_j\right) - ln\left(hR_i^B\right)\right]}{(\sigma^B)^2} > 0 \tag{14}$$

$$\frac{\partial v}{\partial \varphi_j} = \phi(Y)\frac{-1}{\sigma^B\left(R_i^B + \varphi_j\right)} < 0 \tag{15}$$

Given $\sigma_H^B < \sigma_L^B$ and $\varphi_H > \varphi_L$, $v_H < v_L$, and holding all else constant, the high-type buying agent has a lower probability of losing clients than the low-type buying agent.

Taking the second-order of the cross-partial derivatives of equation (12) yields:

$$\frac{\partial^2 \pi_{Sa}}{\partial h \partial v} = -\alpha n\widehat{R_i^B}[1 - \Phi(X)] + \frac{\alpha n\widehat{R_i^B}}{\sigma^S}\phi(X) < 0 \tag{16}$$

Given $v_H < v_L$, $\left(\frac{\partial \pi_{Sa}}{\partial h}\middle|Q_H\right) > \left(\frac{\partial \pi_{Sa}}{\partial h}\middle|Q_L\right)$, and holding all else constant, the high-type buying agent has a higher marginal payoff for each additional p_i^c if $\frac{\partial \pi_{Sa}}{\partial h} > 0$. Therefore, the high-type buying agent has an increased incentive to be self-interested compared with the low-type buying agent if they generate additional payoffs of being self-interested.

Proposition 2: Without binding contracts between buyers and buying agents, the high-type buying agents have lower probabilities of losing clients and higher incentives of being self-interested to gain relatively greater positive returns compared to the low-type buying agents.

4. Sample and Data

Our initial sample consists of 1,553,099 (both sold and expired) listings records of single-family houses listed on the local MLS (Multiple Listing Service), consisting of 17 regions, between January 1994 and December 2017 from the Greater Montreal Real Estate Board (Chambre Immoiliere du Grand Montreal). After deleting incomplete, missing, or illogical observations (i.e., building size exceeds lot size) and non-arm's length transactions (i.e., selling price, or original or last asking price lower than

$10,000), our final sample consists of 1,459,449 listings, including 864,502 sold listings and 594,947 expired listings.

Our data include property characteristics such as house size, age, location, number of rooms, number of bedrooms and bathrooms, number of garages, and property and building types. In addition, our transaction records include initial and last asking prices, selling prices, the agent code of each listing and buying agents, and listing, selling, and expiring dates.

We identify each agent by a unique agent code and use that code to gather the listing and purchasing records of that agent. In our model, high-type buying agents are able to predict the reservation prices of the two parties to a housing transaction more accurately and have stronger impacts on buyers. As both agents' ability and buyers' and sellers' reservation prices are unobservable, we are unable to construct direct measures for these two components separately. Following prior studies on differences in agents' ability and experience (e.g., Agarwal et al., 2019, Turnbull et al., 2021), we differentiate the type of buying agents based on three criteria: the annual average number of purchases the buying agent was involved in the prior 5 years (*Av#Purchases*), the annual average market share based on the total dollar amount of purchases the buying agent was involved in the prior 5 years (*AvMkt%BuyAmt*), and the annual average market share based on commissions the buying agent earned in the prior 5 years (*AvMkt%Commission*). We examine alternative measures for agent type in the robustness check and find consistent results. *Av#Purchases* is the exponential weighted average number of purchases that the buying agent was involved in during the prior 5 years.[17] We use exponential weighted averages to emphasize the importance of activities in recent years on determining the type of buying agents. Similarly, *AvMkt%BuyAmt* (*AvMkt%Commission*) is the exponential weighted average of the market share based on the total dollar amount of purchases the buying agent was involved in (the commissions the buying agent earned) in the same region during the prior 5 years.

Because only 20,137 listing records exist before 2000 and less than 10 listing records are available after 2017 and our proxy types for buying agents are based on the most recent five years in the past, the sample period for the main models are between January 2005 and December 2017. During this sample period, we have a total of 963,926 observations, consisting of 509,713 that were sold and 454,213 that were expired. Since confidence intervals become smaller with larger sample sizes, it becomes

[17] We calculate the annual average number of house purchases that the buying agent was involved in at the transaction date of the subject transaction. If the agent only works for 4 years, we consider the average over the prior 4 years.

increasingly more likely to reject the null hypothesis as the sample size increases for a given level of significance. To deal with this potential inference bias, we use more stringent significance levels, such as 0.5%, 1%, and 5%, when drawing inferences.

Appendix 1 illustrates the definitions of the key variables. Table 1 summarizes the descriptive statistics of our main variables. In Panel A, a typical single-family house in Quebec has an initial asking price of \$229,000, a last asking price of \$199,900, and a final sale price of \$180,000. In Panel B, a typical buying agent in each year is involved in eight purchases, contributes to about 0.11% of the market transactions in terms of the total dollar amount, and earns 0.10% of the market commissions of all buying agents. In panel C, more than 75% of the single-family houses were sold at prices below their last asking prices (the ratio of sale price to last asking price is 0.98 at the 75 percentile). In panel D, a typical listing has only one listing agent and one buying agent, consistent with an assumption in our model.

[Table 1 about here.]

5. Simulation

Due to lack of data on contractual relationships between buyers and buying agents, we are unable to test proposition 1 directly with our data. To provide insights on the model's predictions, we simulate the activities of buyers, sellers, and their agents in a one-stage take-it-or-leave-it (TILI) negotiation. Our goal is to show whether a non-binding contractual relationship imposes an implicit constraint on the buying agent's activities in suggesting an offer price and how sensitive the binding power of that constraint is to changes in φ, σ^S, σ^B, and α.

In the simulation, we randomly draw 10,000 values for the buyer's reservation price (R_i^B), the seller's reservation price (R_i^S), the asking price of the house (p_i^a), the buying agent's prediction of the buyer's reservation price ($\widehat{R_i^B}$), and the buying agent's prediction of the seller's reservation price ($\widehat{R_i^S}$). Based on those values, we simulate the TILI negotiating stage and record the buying agent's proposed offer prices (p_i^c), the offer price parameters ($c\ and\ h$), and the buying agent's payoffs (π_{sa}).

Based on the assumptions in section 3, we conduct the following simulation steps:

Step1: We randomly draw R_i^B and R_i^S based on their distribution: $lnR_i^B \sim N(12.07, 0.61^2)$ and $lnR_i^S \sim N(12.32, 0.59^2)$ where 12.07 (12.32) and 0.61 (0.59) are the mean and the standard deviation of the natural log of final sale prices (initial asking prices) in our dataset. In this round, only the pair of R_i^B and R_i^S that satisfies $R_i^B > R_i^S$ would be kept because a negotiation is successful only if $R_i^B > R_i^S$.

Step 2: We randomly draw p_i^a based on its distribution: $lnp_i^a \sim N(12.20, 0.63^2)$ where 12.20 and 0.63 are the mean and the standard deviation of the last asking prices in our dataset. In our dataset, less than 10% of the houses are sold at a sale price above the asking price, indicating that more than 90% of the buyer's reservation prices are lower than the asking prices of the houses. We adjust the distribution of the asking price accordingly: $lnp_i^a \sim N(12.20 + lnR_i^B - 11.403, 0.63^2)$, so that there is at least a 90% chance that the asking price is above the buyer's reservation price. 11.403 is the 10th percentile of the non-adjusted normal distribution of the asking price ($N(12.20, 0.63^2)$). In this round, only p_i^a that satisfies $p_i^a > R_i^S$ is kept because sellers would not set an asking price below their reservation prices.

Step3: We randomly draw $\widehat{R_i^B}$ and $\widehat{R_i^S}$ based on their distributions: $ln\widehat{R_i^B} \sim N(lnR_i^B, 0.50^2)$ and $ln\widehat{R_i^S} \sim N(lnR_i^S, 0.50^2)$ where 0.50 is the measure of the prediction accuracy of the buying agent in the base-case scenario. We assume that an agent has the same accuracy for predicting both the buyer's and seller's reservation prices ($\sigma^S = \sigma^B = 0.50$)[18]. Only the pair of $\widehat{R_i^B}$ and $\widehat{R_i^S}$ that satisfies $\widehat{R_i^B} > \widehat{R_i^S}$ is kept in each iteration, guaranteeing a positive probability for a successful negotiation.

Step 4: Following steps 1-3, we simulate the payoffs for each participant with and without a binding contract between buyers and buying agents.

***5.1 Scenario with a binding contract between the buyer and the buying agent*:**

In this scenario we randomly draw the offer price parameter, c, based on a uniform distribution: $c \sim U(1, \widehat{R_i^B}/\widehat{R_i^S})$. Then we calculate the offer price $p_i^c = c \times \widehat{R_i^S}$. In the negotiation stage, the buyer accepts the asking price if $p_i^a \leq R_i^B$, and the payoff for the buying agent is $\pi_{sa} = \alpha \times p_i^a$. In the base-case scenario, we set up the commission rate split to the buying agent as $\alpha = 0.025$,[19] which is the mean of commission rate splits in our sample. If $p_i^a > R_i^B$, the buyer proposes the offer price p_i^c suggested by the buying agent. If $p_i^c \geq R_i^S$, the seller accepts the offer price p_i^c, and the payoff for the

[18] Please see Panel C in Figure 1 for the sensitivity tests for σ^S & σ^B.
[19] Please see Panel D in Figure 1 for the sensitivity tests for α.

buying agent is $\pi_{sa} = \alpha \times p_i^c$. If $p_i^a > R_i^B$ and $p_i^c < R_i^S$, the seller rejects the offer price p_i^c, and the payoff for the buying agent is $\pi_{sa} = 0$.

***5.2 Scenario without a binding contract between the buyer and the buying agent*:**

In this scenario we randomly draw the offer price parameter, h, based on a uniform distribution: $h \sim U(\widehat{R_i^S}/\widehat{R_i^B}, 1)$. We then convert the simulated h to c ($c = h \times \widehat{R_i^B}/\widehat{R_i^S}$) to compare with the previous (binding contract) scenario, so that the offer price $p_i^c = c \times \widehat{R_i^S}$.

In the negotiation stage, the buyer accepts the asking price if $p_i^a \leq R_i^B$, and the payoff for the buying agent is $\pi_{sa} = \alpha \times p_i^a$. If $p_i^a > R_i^B$, the buyer proposes the offer price suggested by the buying agent. If $p_i^c > R_i^B + \varphi \times R_i^B$, the buyer rejects the buying agent's suggested offer price and engages with other buying agents. In this case, the payoff for the buying agent is $\pi_{sa} = 0$. If $p_i^c \leq R_i^B + \varphi \times R_i^B$, the buyer accepts the buying agent's suggestion and proposes an offer with price p_i^c. For the base-case binding-contract scenario, we set the tolerance level, $\varphi = 10\%$.[20] If $p_i^c \geq R_i^S$, the seller accepts the offer price p_i^c, and the payoff for the buying agent is $\pi_{sa} = \alpha \times p_i^c$. If $p_i^a > R_i^B, p_i^c \leq R_i^B + \varphi \times R_i^B, and\ p_i^c < R_i^S$, the seller rejects the offer price p_i^c, and the payoff for the buying agent is $\pi_{sa} = 0$.

Step 5: We plot the relationship between the offer parameter, c, and the payoff of the buying agent, π_{sa}, under both the contract and no contract scenarios. We also test the sensitivity of the simulation results with regard to the change of the walk-away tolerance level of the buyer to the buying agent (φ), the accuracy of the buying agent on predicting the buyer's and seller's reservation prices ($\sigma^S = \sigma^B$), and the commission rate splits to the buying agent (α).

Figure 1 graphically displays the simulation results. In all the scenarios examined, the non-linear relation between the buying agent's payoff and the offer parameter is higher given a legally binding or explicit contractual relationship between the buyer and the buyer's buying agent, supporting the first proposition in our model. In Panel A of Figure 1, we show the quadratic plot of the base-case relationship between c (offer price parameter) and π_{sa} (buying agent's payoff) for the explicit and implicit contractual scenarios where $\varphi = 10\%, \sigma^S = \sigma^B = 0.50, \alpha = 0.025,$ $and\ w \neq 0$.[21] The

[20] Please see Panel B in Figure 1 for the sensitivity tests for φ.
[21] Linear plots of the relationship between c and π_{sa} under the two scenarios also are reported in the Online Supplementary Appendix 3 (OSA 3).

offer price parameter (c) on the X-axis is bound between 1 and $\widehat{R_i^B}/\widehat{R_i^S}$. Consistent with Proposition 1, Panel A of Figure 1 indicates that when the buyer and the buying agent's relationship is bound by a contract (see the dash line), the buying agent achieves higher payoffs by proposing a higher offer price to the buyer, which conflicts with the best interests of the buyer who wants to buy at a lower price. In the absence of a contract, the buying agent's payoff increases with increases in the proposed offer price (see the solid line) but at a lower increasing rate compared with that in the presence of a contract (see the dash line). In OSA 3, we show that our simulation results when plotted are consistent with Proposition 1. Compared to Panel A and varying one parameter at a time, we observe that the binding power of the implicit constraint created by a non-binding contract between the buyer and the buying agent increases with an decrease in the tolerance level (Panel B), decrease in the prediction accuracy of the buying agent (Panel C), and increase in the commission rate split to the buying agent (Panel D).

6. Empirical Analyses

The above simulation exercise tests Proposition 1. To test Proposition 2 in the model, we empirically examine whether and how agent experience affects transaction outcomes given conflicts of interests between buyers and their buying agents in the absence of a binding contract. After estimating the predicted buying and asking prices for properties, we then show that transactions undertaken by high- versus low-type buying agents have less favorable transaction outcomes for buyers in terms of the ratio of the final sale price to the last asking price (*SPtoLastAP*). This is followed by a set of robustness checks dealing with selection bias, omitted variable bias, brokerage firms, listing agents, and property fixed effects, past bargaining performance of buying agents, alternative measure of transaction outcomes (*lnSP* and *SPtoOriginalAP*), alternative criteria for determination of agent type, market size subsamples, and a system of simultaneous equations model. We end with the conclusion that our baseline inferences are unchanged.

6.1 Relation between Buying Agent Type and the Transaction Outcome

We run the following ordinary least square (OLS) model to examine the impact of a buying agent's type on the ratio of a house's final sale price to its last asking price (*SPtoLastAP*). Replacing *SPtoLastAP* with the final sale price (*lnSP*) and the ratio of the final sale price to the original asking price (*SPtoOriginalAP*) yields consistent results.

$$SPtoLastAP_i = \alpha_0 + \beta(Agent's\ Type\ Proxy) + \sum \alpha_j (Main\ Controls)_i$$
$$+ House's\ Characteristics + Listing\ Agent's\ Characteristics$$
$$+ F_{Year} + F_{Month} + F_{Region} + \delta_i \tag{17}$$

We expect that high-type buying agents are able to predict the buyer's and seller's reservation prices more accurately and receive higher tolerance levels from their clients due to their stronger impacts on buyers. As described in Section 4, we construct three proxies for the type of a buying agent: the annual average number of purchases (*Av#Purchases*), the annual average market share based on the dollar amounts of purchases (*Av%MktBuyAmt*), and the annual average market share based on the commissions earned (*Av%MktCommission*).

We follow prior studies and include a set of standard controls for housing characteristics (or predicted value), time on the market, the number of agents, agent's listing inventory, agent attributes, brokerage firm attributes, degree of overpricing, and contract duration.[22] $Main\ Controls$ include $YhatHeckman_i$, the predicted selling price from the Heckman model.[23] $ln(MOM)$ indicates the natural log of listing months on the market. $\#ListingAgents_i$ and $LABusyness_i$ represent the number of listing agents involved in transaction *i* and the number of active listings of the listing agent involved in transaction *i* during the contract period leading up to the house purchase. $\#SellingAgents_i$ and $BABusyness_i$ represent the number of buying agents involved in transaction *i* and the number of active purchases of the buying agent with purchase dates within 180 days after the purchase date of transaction *i*. We use 180 days because the average pre-purchase period is about half a year and we expect that buying agents will share their energy among potential transactions with overlapping pre-purchase periods. $DegreeOverpricing_i$ is the degree of overpricing based on the last asking price as measured by the flexible general least square (FGLS) model.[24] $ContractDuration_i$ is the duration of the selling contract between listing agents and a seller. $DumPriceInc_i$,

[22] The standard controls include house characteristics, time on the market, listing agent's attributes, and listing office's attributes (e.g., Barwick et al., 2017; Turnbull and Waller, 2018). In addition to the standard controls, Lin et al. (2018) also include the duration of the listing contract between sellers and listing agents. Anglin and Springer (2003) and Rutherford et al. (2005) include the degree of overpricing for houses. Buccianeri and Minson (2013) include the predicted value in addition to the general controls.
[23] We report the estimation model and results for the predicted selling price in the Online Supplementary Appendix 4 (OSA 4).
[24] We report the estimation model and results for the predicted asking price and the degree of overpricing ($DegreeOverpricing_i$) in the Online Supplementary Appendix 4 (OSA 4).

$DumPriceDec_i$, and $DumUrban_i$ are dummy variables for asking price increase, asking price decrease, and urban, respectively. $DumDualAgent_i$ is the dummy variable for a dual-agent situation which equals one when the listing agent and the buying agent are the same person; otherwise, it is equal to zero. $DumTopLABrokerage_i$ and $DumTopBABrokerage_i$ are dummy variables for top listing brokerage firms and top buying brokerage firms, respectively. $House's\ characteristics$ include the house's size, age, number of bedrooms and bathrooms, number of driveways and garages, and building type and property type. $Listing\ agent's\ characteristics$ include listing agents' active years, past transaction volumes, and successful sales rates. F_{Year}, F_{Month}, and F_{Region} are year, month, and region fixed effects. The standard errors are clustered at the FSA level.

Consistent with Proposition 2, coefficients reported in Table 2 indicate that under the fixed percentage commission system (FPCS), buying agents who have high past purchases expertise (*Av#Purchases*) and share high percentages of the total market based on purchase amounts (*AvMkt%BuyAmt*) and commissions (*AvMkt%Commission*) are significantly associated with a higher ratio of the final sale price to the last asking price (*SPtoLastAP*). This implies that buyers who are served by a high-type buying agent pay more relative to the last asking price, given the completion of a sale. In terms of economic significance, a one-standard-deviation increase in *Av#Purchases* increases *SPtoLastAP* by 0.012% (Column 1) or 0.014% (Column 2), which represents an increase in the final sale price of $308 (Column 1) or $359 (Column 2) when evaluated at the average last asking price in our sample. A one-standard-deviation increase in *AvMkt%BuyAmt* increases the ratio of the final sale price to the last asking price (*SPtoLastAP*) by 7.928% (Column 3) or 9.384% (Column 4). A one-standard-deviation increase in *AvMkt%Commission* increases the *SPtoLastAP* by 5.688% (Column 5) or 6.506% (Column 8). These results are consistent with our model prediction that high-type buying agents have an incentive to induce higher sale prices. This is a downward biased estimate since it does not include unobservable situations where the buyer had moved to another buying agent who helped conclude a transaction for the migrating buyer. Although these economic effects in terms of dollar amounts per transaction do not seem large, the estimated aggregate wealth transfer from buyers to sellers per year is $13.08 million. This represents an incremental aggregate commission of $653,810 paid to both listing agents and buying agents (or $326,905 paid to buying agents based on an assumed 50-50 commission split). These results are consistent with our theoretical proposition (Proposition 2) in the accuracy version and the tolerance version where high-type buying agents are more likely to suggest higher offer prices and participate in transactions at higher final sale prices and therefore higher *SPtoLastAP*. Although the absence of a binding contract creates a constraint on the buying agent's self-interest behavior because buyers can walk away easily, the binding power of this principal-agent relationship is weaker for high-type buying agents.

[Table 2 about here.]

We conduct several robustness tests for our main results. First, we conduct the two-step Heckman selection model (Heckman, 1979) to check for selection bias. Second, we follow the approach in Oster (2015) to check for omitted variable biases. Third, we control for the listing agent and the buying agent brokerage firm fixed effects, the listing agent fixed effects, and the property fixed effects, respectively. Fourth, we control for the buying agent's past performance as proxied by their past *SPtoLastAP* as the listing agent and the buying agent, respectively. Then, we examine the stability of our main results by using the alternative outcome variables, including the natural log of the final sale price (*lnSP*) and the ratio of the final sale price to the initial asking price (*SPtoOriginalAP*), and alternative proxies of agent heterogeneity.[25] We also conduct several sub-sample tests: the Montreal region, which is the financial center in the province of Quebec, versus the other 16 regions in Quebec, the Big-Six (i.e., six cities with the greatest population) versus Non-Big-Six, the Top5 regions (i.e., the five regions with the most listings) versus the Non-Top5 regions. Last, we use a three-stage least squares model to mitigate any concerns about reversal causality between the *SPtoLastAP* and the listing time on the market (Turnbull and Dombrow, 2006; Waller and Jubran, 2012; Turnbull and Waller, 2018).

We summarize these robustness results in the Online Supplementary Appendix 5 (OSA 5). All the results of above robustness checks confirm our baseline results, which indicates high-type buying agents are associated with a higher ratio of a house's final sale price to its last asking price, suggesting a weaker binding power for high-type buying agents under FPCS.

6.2 Different Binding Forces between Low- and High-type Agents

[25] Alternative agent heterogeneity proxies include the annual average number of purchases the buying agents was involved in the prior 3 years (*Av#Purchases3Yrs*) and in the prior year (*Av#Purchases1Yr*), the annual average market share based on purchase amounts in the prior 3 years (*AvMkt%BuyAmt3Yrs*) and in the prior year (*AvMkt%BuyAmt1Yr*), the annual average market share based on the commission earned in the prior 3 years (*AvMkt%Commission3Yrs*) and in the prior year (*AvMkt%Commission1Yr*), the annual average number of transactions (both listings and purchases) the buying agent was involved in the prior 5 years (*Av#Transactions*), and the annual average success rate of listings the buying agent was involved in the prior 5 years (*Av%SuccessSale*).

In this section, we further examine different binding forces between low- and high-type buying agents that can arise from information asymmetry, agent incentives, and collusion opportunities. We assume that information asymmetry increases the volatility of the buying agent's appraisal of house value and creates barriers for the buying agent to predict the buyer's reservation prices. We use the commission splits to buying agents to estimate the commission rate and the dual-agent opportunity to estimate the collusion opportunity.

6.2.1 Information Asymmetry

When information about market conditions and the market value of a house is limited, it is more difficult for the buying agent to predict the buyer's and the seller's reservation prices. Thus, σ_B and σ_S are higher in a market with high information asymmetry, which weakens the no-contract binding force on the high-type buying agent and results in a worse outcome for the buyer. In addition, the buyer's tolerance level for the high-type buying agent might be even higher in markets with high information asymmetry, further weakening the no-contract binding force on this agent type. We construct four proxies for the level of information asymmetry: an atypicality index, first-time house listing, and the house's age and value. The level of information asymmetry associated with an atypical house is higher than that in the rest of the housing market because only a few comparable houses are available for analyses each year. The same expectation is made for first-time listed houses, old houses, and high-value houses.

We follow prior studies (e.g., Haurin, 1988; Glower, Haurin, and Hendershott, 1998; Bar-Isaac and Gavazza, 2015) and calculate an atypicality index, which is the aggregated value of the difference between the house's characteristics and the sample mean of each characteristic. The atypical dummy variable, $DumATYP$, is equal to one when a house's atypicality index is in the top five percentile in its region.

For each listing, we calculate the number of transactions for the house in the previous ten years. The window for housing transaction history is between January 2002 and December 2011 and our test period is between January 2012 and December 2017. $Dum1stListing$ is a dummy variable that is equal to one when the house is listed on the market for the first time; otherwise, it is equal to zero.

The age dummy variable, $DumOldAge$, is equals to one when the house's age is in the top five percentile in its region in a given year; otherwise, it is equal to zero. Similarly, the value dummy, $DumHighValue$, is equals to one when the house's hedonic price is in the top 5 percentile in its region in a given year; otherwise, it is equal to zero.

In Table 3, the negative and significant coefficients for the atypical dummy, the listing frequency dummy, the age dummy, and the value dummy indicate that atypical houses, first-time-listed houses, old houses, and high-value houses experience lower ratios of the final sale price to the last asking price ($SPtoLastAP$) than other houses. Consistent with results reported in Table 2 and our model prediction, the significantly positive coefficients for the interaction terms between the agent heterogeneity proxies and the information asymmetry proxies for atypical houses and high-price houses indicate that buyers using high-type buying agents end up with less favorable outcomes in markets with high information asymmetry. For example, Column 1 in Panel A indicates that a one-standard-deviation increase in *Av#Purchases* is associated with a 0.013% increase in *SPtoLastAP* for atypical houses. This represents an additional increase in the final sale price of $334 when evaluated using the average last asking price in our sample. The economic significance based on *AMkt%BuyAmt* and *AvMkt%Commission* is $544 and $490, respectively.

[Table 3 about here.]

6.2.2 Agent Incentives

In this section, we examine how commission rate splits and the fixed amount commission system (FACS) effects on transaction outcomes are moderated by buying agent heterogeneity. We include the commission dummy variable ($DumHighCom$), the FACS dummy variable ($DumFixCom$), and their interaction terms with the type proxies for buying agents, respectively. $DumHighCom$ is equal to one for commission rate splits to buying agents above 2.5% (the mean of the commission rate splits in our sample); and equal to zero otherwise. $DumFixCom$ is equal to one if agents in the transactions are compensated using the FACS; and equals zero otherwise.

In Panel A of Table 4, the negative coefficients for $DumHighCom$ suggests a lower average ratio of the final sale price to the last asking price ($SPtoLastAP$) when the buying agents expect to receive a high commission rate. This result could be explained by impatient sellers who offer higher commissions and accept lower sale prices to sell faster (Barwick and Wong, 2019). The coefficient estimates for the three high-type proxies are still positive and statistically significant. In addition, the positive coefficients for the interaction terms of the type proxies for buying agents and the commission rate dummy suggest that high commission rate splits are associated with an even worse outcome for the buyer when dealing with a high-type buying agent due to this agent's lower probability of losing clients. For example, Column 2 (3) in Panel A indicates that a one-standard-deviation increase in *AvMkt%BytAmt* (*AvMkt%Commission*) is associated with an increase of *SPtoLastAP* by 23.47% (19.633%) for transactions that splits more than a 2.5% commission rate to buying agents, representing an additional $819 ($634) increase in the final sale price when evaluated using the average last asking price in our sample.

[Table 4 about here.]

In Panel B of Table 4, the positive coefficients for $DumFixCom$ indicate a higher average ratio of the final sale price to the last asking price ($SPtoLastAP$) when agents receive a constant amount of commission under the FACS. In addition, the negative coefficients for the interaction terms consisting of the buying agent's type proxies and the FACS dummy variable suggest that high-type buying agents are more likely to be bound by the no-contract constraint under the FACS than under the FPCS. This result implies that the FACS helps to mitigate the conflict of interest between buying agents and their buyer clients. For example, Column 2 (3) in Panel B indicates that a one-standard-deviation increase in *AvMkt%BytAmt* (*AvMkt%Commission*) decreases *SPtoLastAP* by 23.79% (30.63%) for transactions that pay buying agents fixed amount commissions, reducing the total effect to 14.86% (23.77%). This represents a reduction of $519 ($767) in the buyer's purchase price when evaluated at the average last asking price in our sample. This finding is consistent with the findings in Sahin et al. (2013).[26]

6.2.3 Collusion Opportunities

In this section, we examine the impact of collusion opportunities. We conjecture that in intra-office transactions (when the buying agent and the listing agent are from the same brokerage office), the buying agent has a greater opportunity to collude with the listing agent. Similar situations may occur in intra-firm transactions (when the buying agent and the listing agent work for the same brokerage firm).

[26] The alternative commission system applied in Sahin et al. (2013) is introduced by Yavas and Colwell (1999), which is not the same as the FACS in this paper. Under their alternative commission system, the seller pays the listing agent a fixed percentage of a predetermined fixed amount of commission and the buying agent receives the rest of the predetermined total commission.

We therefore include the intra-office dummy ($DumIntraOffice$) and the intra-firm dummy ($DumIntraFirm$), and their interaction terms with the type proxies for buying agents, respectively. $DumIntraOffice$ equals one for an intra-office transaction; and equals zero otherwise. $DumIntraFirm$ equals one for an intra-firm transaction; and equals zero otherwise. We also add a control for dual-agent transactions (when the buying agent and the listing agent are the same person) in our model.

In Table 5, the negative coefficients for the intra-office dummy and the intra-firm dummy indicate favorable outcomes to the buyer but unfavorable outcomes to the seller, consistent with the prior literature (Gardiner, Heiser, Kallberg, and Liu, 2007; Brastow and Waller, 2013; Kadiyali, Prince, Simon, 2014; and Johnson, Lin, Xie, 2015; etc.). In addition, the positive coefficients for the interaction terms of the buying agent's type proxies and the collusion opportunity dummy suggest that buyers end up with even worse outcomes with the presence of high-type buying agents in transactions with high collusion possibilities. For example, Column 1 in Panel A indicates that a one-standard-deviation increase in *Av#Purchases* increases *SPtoLastAP* by an additional 0.009% for intra-office transactions. This represents an additional $231 increase in the final sale price when evaluated at the average last asking price in our sample. The economic significance based on *AMkt%BuyAmt* and *AvMkt%Commission* is $475 and $489, respectively. This finding is consistent with our model predication that the high-type agent has a stronger impact on both buyers and sellers and can more accurately predict seller's and buyer's reservation prices.

[Table 5 about here.]

7. Conclusion

Unlike home sellers, home buyers have an obvious directional conflict of interest with their agents regarding the final sale prices under the fixed percentage commission system (FPCS). This paper uses a model to examine if the efficiency and fairness of the FPCS for buyers is enhanced when a non-contractual relationship exists between buyers and their buying agents (i.e., no-contract constraint). We show that this no-contract constraint can better align the buying agent's interests with those of buyers under the FPCS (Proposition 1). Our simulation results support Proposition 1. We also introduce agent heterogeneity which plays an important role in determining the strength of the binding force in the absence of a binding contract. High-type buying agents have lower probabilities of losing clients and higher incentives of being self-interested compared to low-type buying agents (Proposition 2). Our reduced-form analyses support Proposition 2. We also empirically test the effects of agent type under various binding forces arising from information asymmetry, agent incentives, and collusion opportunities.

Our study can be extended in several ways using more comprehensive data. First, one could directly test the efficiency of the FPCS with non-contract bounds (Proposition 1) using data on contractual relationships between buyers and buying agents (indicating who signs a binding contract with the buying agent and who does not). Second, one could empirically examine selection and survivorship biases from using only complete transactions given access to data on incomplete transactions and failed bids associated with buying agents.

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Table 1: Summary Statistics

	Obs.	Mean	Median	25%	75%	S.D.
Panel A: House characteristics (1994-2017)						
Sale price ($, thousands)	864,502	210.84	180.00	122.00	254.00	159.77
Log of sale price	864,502	12.07	12.10	11.71	12.45	0.61
Original asking price ($, thousands)	1,223,451	270.32	229.00	159.90	315.00	221.66
Log of original asking price	1,223,451	12.32	12.34	11.98	12.66	0.59
Last asking price ($, thousands)	1,459,449	244.27	199.90	139.00	289.00	205.90
Log of last asking price	1,459,449	12.20	12.21	11.84	12.57	0.63
Building size (sqft, thousands)	1,264,653	1.11	1.01	0.82	1.25	0.52
Lot size (sqft, thousands)	1,402,527	16.89	7.28	5.28	15.10	32.47
Total # of bedrooms	1,459,449	3.34	3.00	3.00	4.00	1.03
Total # of bathrooms	1,459,449	1.47	1.00	1.00	2.00	0.64
Total # of garages	1,304,669	0.70	1.00	0.00	1.00	0.82
Total # of driveways	1,304,669	3.27	3.00	2.00	4.00	2.17
House age at listing sold/ expired (years)	1,193,874	29.09	24.00	11.00	41.00	24.55
Forced air conditioner (dummy)	1,446,081	0.22	0.00	0.00	0.00	0.42
Electronic baseboard (dummy)	1,446,081	0.47	0.00	0.00	1.00	0.50
Irregular building (dummy)	1,459,449	0.26	0.00	0.00	1.00	0.44
Irregular lot (dummy)	1,459,449	0.28	0.00	0.00	1.00	0.45
Panel B: Buying Agent Heterogeneity (2005-2017)						
Average # of purchases involved prior 5 years	507,082	10.62	8.00	4.02	13.95	9.78
Average market share of buying agent based on purchase amounts in prior 5 years (%)	432,607	0.40	0.11	0.04	0.30	1.33
Average market share of buying agent based on commission earned in prior 5 years (%)	381,923	0.34	0.10	0.02	0.25	1.23
Average # of transactions (both listings and purchases) involved prior 5 years	504,016	33.22	22.80	10.79	43.00	34.46
Successful sales ratio in prior 5 years	490,923	0.53	0.56	0.43	0.68	0.22
Panel C: Transaction Outcomes (2005-2017)						
Sale price to original asking price	509,542	0.93	0.94	0.90	0.97	0.67
Sale price to last asking price	509,713	0.95	0.96	0.93	0.98	0.49
Listing time on market (MOM, months)	963,626	5.06	4.10	1.67	6.75	4.52
Sale price ($, thousands)	509,713	249.07	215.00	155.90	290.00	180.42
Log of sale price	509,713	12.26	12.28	11.96	12.58	0.57
Last asking price ($, thousands)	509,713	262.35	225.00	164.90	299.90	194.18
Sold dummy (=1, sold; =0, expired)	963,626	0.53	1.00	0.00	1.00	0.50
Panel D: Other Control Variables (2005-2017)						
Predicted sale price ($, thousands)	659,795	302.93	259.25	198.23	352.14	182.62
Ln(predicted sale price) (Heckman model)	659,795	12.50	12.47	12.20	12.77	0.47
Ln(MOM)	963,626	1.11	1.41	0.51	1.91	1.23
# of listing agents involved	963,626	1.33	1.00	1.00	2.00	0.55

# of buying agents involved	509,713	1.10	1.00	1.00	1.00	0.36
Buying agent active years (years)	507,082	6.81	6.34	3.16	9.89	4.41
Listing agent busyness	963,626	28.84	16.00	6.00	36.00	38.61
Buying agent busyness	507,082	22.29	13.00	5.00	29.00	27.89
Degree of overpricing (DOP)	659,944	0.005	0.008	-0.151	0.157	0.31
Contract duration (months)	963,626	7.64	6.37	5.07	9.87	4.33
Last AP > Original AP (dummy)	963,281	0.02	0.00	0.00	0.00	0.14
Original AP > Last AP (dummy)	963,281	0.36	0.00	0.00	1.00	0.48
Dual-agent (dummy)	507,082	0.41	0.00	0.00	1.00	0.49
Urban location (dummy)	963,626	0.71	1.00	0.00	1.00	0.45
Top 6 buying brokerage (dummy)	507,082	0.81	1.00	1.00	1.00	0.39
Top 6 listing brokerage (dummy)	963,626	0.82	1.00	1.00	1.00	0.39
Listing agent active years (years)	963,626	7.59	7.17	3.89	10.86	4.61
Listing agent's average # of transactions involved prior 5 years	961,150	42.58	29.75	14.95	55.67	41.67
Listing agent's successful sales ratio in prior 5 years	963,626	0.54	0.55	0.42	0.67	0.20
Buying agent's past bargaining performance as buying agents	431,201	0.95	0.95	0.94	0.96	0.02
Buying agent's past bargaining performance as listing agents	371,826	0.95	0.95	0.93	0.96	0.02
Atypical houses (dummy)	659,795	0.05	0.00	0.00	0.00	0.22
High-value houses (dummy)	659,795	0.05	0.00	0.00	0.00	0.22
First listed houses (dummy)	510,408	0.47	0.00	0.00	1.00	0.50
Old-age houses (dummy)	811,027	0.05	0.00	0.00	0.00	0.21
Commission rate splits to buying agents (%)	933,005	2.43	2.50	2.00	2.50	0.40
High commission rate (dummy, >2.5%)	933,005	0.19	0.00	0.00	0.00	0.39
Fixed amount commission (dummy)	963,198	0.03	0.00	0.00	0.00	0.17
Intra-firm (dummy)	509,713	0.09	0.00	0.00	0.00	0.29
Intra-office (dummy)	509,713	0.08	0.00	0.00	0.00	0.27

Notes: This table reports summary statistics for house characteristics, our main testing variables: *Buying Agent Heterogeneity*, dependent variables: *Transaction Outcomes*, and main control variables.

Table 2: Agent Heterogeneity and Sale Price to Last Asking Price, 2005-2017

Dependent Variable:	SalePrice/LastAP (SPtoLastAP)					
	(1)	(2)	(3)	(4)	(5)	(6)
Av#Purchases	0.00012***	0.00014***				
	(5.15)	(6.00)				
AvMkt%BuyAmt			0.07928**	0.09384**		
			(2.64)	(2.74)		
AvMkt%Commission					0.05688*	0.06506*
					(2.16)	(2.30)
PredSalePrice		0.00741***		0.00784***		0.00754***
		(6.78)		(7.06)		(6.58)
Ln(MOM)	-0.00800***	-0.00800***	-0.00799***	-0.00800***	-0.00792***	-0.00792***
	(-41.48)	(-44.66)	(-41.51)	(-44.68)	(-39.24)	(-42.40)
#ListingAgents	0.00053*	0.00068*	0.00039	0.00056	0.00029	0.00041
	(2.46)	(2.46)	(1.64)	(1.86)	(1.24)	(1.42)
#BuyingAgents	0.00087*	0.00061	0.00068	0.00043	0.00079	0.00054
	(2.27)	(1.50)	(1.64)	(0.97)	(1.85)	(1.17)
#ActiveYrs	-0.00004*	-0.00006**	-0.00004	-0.00006*	-0.00006**	-0.00007***
	(-2.10)	(-2.65)	(-1.94)	(-2.39)	(-2.76)	(-3.06)
LABusyness	0.00000	-0.00001	-0.00001	-0.00002	-0.00001	-0.00001
	(0.14)	(-0.84)	(-0.95)	(-1.79)	(-0.81)	(-1.67)
BABusyness	-0.00004***	-0.00004***	-0.00002***	-0.00002**	-0.00002***	-0.00002*
	(-5.02)	(-5.17)	(-3.19)	(-2.78)	(-2.91)	(-2.44)
DOP	0.01276***	0.00818***	0.01313***	0.00888***	0.01267***	0.00823***
	(7.53)	(4.07)	(7.41)	(4.30)	(6.79)	(3.76)
ContractDuration	0.00023***	0.00014***	0.00027***	0.00018***	0.00027***	0.00017***
	(6.36)	(3.49)	(7.61)	(4.58)	(6.71)	(3.94)
DumPriceInc	0.01197***	0.01384***	0.01188***	0.01380***	0.01225***	0.01414***
	(13.36)	(13.68)	(12.07)	(12.21)	(12.05)	(12.08)
DumPriceDec	0.00801***	0.00787***	0.00797***	0.00784***	0.00787***	0.00775***
	(28.93)	(26.35)	(27.86)	(25.55)	(26.92)	(25.00)
DumUrban	0.00624***	0.00962***	0.00602***	0.00930***	0.00617***	0.00949***
	(3.80)	(4.75)	(3.73)	(4.74)	(3.57)	(4.51)
DumDualAgent	-0.00938***	-0.01095***	-0.00911***	-0.01069***	-0.00900***	-0.01062***
	(-36.76)	(-39.28)	(-33.16)	(-36.01)	(-31.66)	(-34.02)
DumTopBuyingBrokerage	0.00200***	0.00221***	0.00222***	0.00250***	0.00224***	0.00253***
	(7.22)	(7.18)	(7.32)	(7.31)	(7.09)	(7.25)
DumTopListingBrokerage	0.00111**	0.00155***	0.00106*	0.00151***	0.00124***	0.00170***
	(2.81)	(3.62)	(2.59)	(3.40)	(2.93)	(3.74)
House Chara.	Yes	No	Yes	No	Yes	No
Listing Agent Chara.	Yes	Yes	Yes	Yes	Yes	Yes
Year/Month/Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Observations	359,122	359,122	305,141	305,141	270,856	270,856
R-squared	0.18758	0.14260	0.18872	0.14313	0.18498	0.13868

Notes: This table reports results from OLS regressions, testing the impact of the buying agent heterogeneity on the ratio of the final sale price to the last asking price (*SPtoLastAP*). Column 1 and 2 include the annual average number of purchases the buying agent was involved in during the prior 5 years (*Av#Purchases*) as the identifier of buying agent heterogeneity. Columns 3 and 4 include the annual average market shares of the buying agent based on the dollar amounts of purchases during the prior 5 years (*AvMkt%BuyAmt*) as the identifier of buying agent heterogeneity. Column 5 and 6 include the annual average market shares of the buying agent based on the commission earned during the prior 5 years (*AvMkt%Commission*) as the identifier of buying agent heterogeneity. Columns 1, 3, and 5 control for house characteristics. Columns 2, 4, and 6 control for the predicted sale price from the Heckman model. All columns control for listing agent characteristics and year, month, and region fixed effects. We report the t-values in the parentheses based on standard errors clustered at the FSA and the year-month levels. The estimation samples for all models include single-family houses listed on the MLS during the 2005-2017 period. Statistics with significance at 0.5% level are denoted with ***, at 1% level with **, and at 5% level with *.

Table 3: Atypical Houses, Repeat Listings, Old-age Houses, and High-value Houses

Dependent Variable:	SalePrice/LastAP (SPtoLastAP)		
	(1)	(2)	(3)
Panel A: Atypical Houses (2005-2017)			
Av#Purchases	0.00012***		
	(4.89)		
AvMkt%BuyAmt		0.07311*	
		(2.42)	
AvMkt%Commission			0.05239*
			(2.02)
DumATYP	-0.01532***	-0.01507***	-0.01523***
	(-10.49)	(-11.50)	(-11.37)
Av#Purchases × DumATYP	0.00013*		
	(2.19)		
AvMkt%BuyAmt × DumATYP		0.15601***	
		(5.39)	
AvMkt%Commission × DumATYP			0.15172***
			(3.53)
Observations	359,122	305,141	270,856
R-squared	0.19029	0.19153	0.18789
Panel B: Repeat Listings (2012-2017)			
Av#Purchases	0.00008**		
	(2.75)		
AvMkt%BuyAmt		0.07202	
		(1.93)	
AvMkt%Commission			0.07555
			(1.99)
Dum1stListing	-0.00378***	-0.00329***	-0.00328***
	(-11.03)	(-12.30)	(-12.71)
Av#Purchases × Dum1stListing	0.00004		
	(1.99)		
AvMkt%BuyAmt × Dum1stListing		0.00816	
		(0.50)	
AvMkt%Commission × Dum1stListing			0.00042
			(0.03)
Observations	202,915	170,144	163,421
R-squared	0.19622	0.19823	0.19801

Panel C: Old-age Houses (2005-2017)			
Av#Purchases	0.00012***		
	(4.98)		
AvMkt%BuyAmt		0.07983**	
		(2.64)	
AvMkt%Commission			0.05614*
			(2.23)
DumOldAge	-0.01843***	-0.01898***	-0.01902***
	(-17.78)	(-20.34)	(-21.07)
Av#Purchases × DumOldAge	0.00002		
	(0.29)		
AvMkt%BuyAmt × DumOldAge		0.12941*	
		(2.06)	
AvMkt%Commission × DumOldAge			0.05587
			(1.00)
Observations	359,122	305,141	270,856
R-squared	0.16074	0.16164	0.15783
Panel D: High-value Houses (2005-2017)			
Av#Purchases	0.00012***		
	(4.90)		
AvMkt%BuyAmt		0.07313*	
		(2.42)	
AvMkt%Commission			0.05241*
			(2.02)
DumHighValHse	-0.01532***	-0.01509***	-0.01521***
	(-10.47)	(-11.50)	(-11.37)
Av#Purchases × DumHighValue	0.00013*		
	(2.17)		
AvMkt%BuyAmt × DumHighValue		0.15659***	
		(5.43)	
AvMkt%Commission × DumHighValue			0.15228***
			(3.55)
Observations	359,122	305,141	270,856
R-squared	0.19029	0.19153	0.18788
Main Control Variables	Yes	Yes	Yes
House Characteristics	Yes	Yes	Yes
Listing Agent Characteristics	Yes	Yes	Yes
Year/Month/Region FE	Yes	Yes	Yes

Notes: This table repots results from OLS regressions testing the impact of the information asymmetry level on the different binding forces of the no-contract constraint under the FPCS. We use the house's atypicality index, first-time listing frequency, the house's age, and the house's value to proxy information asymmetry level. Panel A reports coefficients for the model including the atypical dummy (*DumATYP*) and its interaction term with *Av#Purchases* (Column 1), *AvMkt%BuyAmt* (Column 2), and *AvMkt%Commission* (Column 3), respectively. Panel B reports coefficients for the model including the first-time listing dummy (*Dum1stListing*) and its interaction term with *Av#Purchases* (Column 1), *AvMkt%BuyAmt* (Column 2), and *AvMkt%Commission* (Column 3), respectively. Panel C reports coefficients for the model including the age dummy (*DumOldAge*) and its interaction term with *Av#Purchases* (Column 1), *AvMkt%BuyAmt* (Column 2), and *AvMkt%Commission* (Column 3), respectively. Panel D reports coefficients for the model including the value dummy (*DumHighValue*) and its interaction term with *Av#Purchases* (Column 1), *AvMkt%BuyAmt* (Column 2), and *AvMkt%Commission* (Column 3), respectively. The dependent variable for all models is the ratio of the final sale price to the last asking price (*SPtoLastAP*). Unreported main controls include *Ln(MOM)*, *#ListingAgents*, *#BuyingAgents*, *#ActiveYrs*, *LABusyness*, *BABusyness*, *DOP*, *ContractDuration*, *DumPriceInc*, *DumPriceDec*, *DumUrban*, *DumDualAgent*, *DumTopBuyingBrokerage*, and *DumTopListingBrokerage*. All columns control for house characteristics, listing agent characteristics, and year, month, and region fixed effects. The estimation samples for Panels A, C, and D cover single-family houses in Quebec listed on the MLS during the 2005-2017 period. The estimation sample for Panel B cover single-family houses in Quebec listed on the MSL during the 2012-2017 period. We report t-values in the parentheses based on standard errors clustered at the FSA and year-month levels. Statistics with significance at 0.5% level are denoted with ***, at 1% level with **, at 5% level with *.

Table 4: Commission Rate and Commission Structure, 2005-2017

Dependent Variable:	SalePrice/LastAP (SPtoLastAP)		
	(1)	(2)	(3)
Panel A: High Commission Rate			
Av#Purchases	0.00011***		
	(4.97)		
AvMkt%BuyAmt		0.07739***	
		(3.63)	
AvMkt%Commission			0.05969***
			(3.18)
DumHighCom	-0.00268***	-0.00309***	-0.00307***
	(-3.43)	(-4.52)	(-4.29)
Av#Purchases × DumHighCom	0.00004		
	(1.05)		
AvMkt%BuyAmt × DumHighCom		0.23470***	
		(6.55)	
AvMkt%Commission × DumHighCom			0.19633***
			(4.81)
Observations	353,115	299,783	266,297
R-squared	0.19001	0.19151	0.18756
Panel B: Fix Commission System			
Av#Purchases	0.00012***		
	(5.36)		
AvMkt%BuyAmt		0.08929***	
		(2.86)	
AvMkt%Commission			0.06856*
			(2.45)
DumFixCom	0.02270***	0.02427***	0.02463***
	(14.04)	(14.72)	(13.71)
Av#Purchases × DumFixCom	-0.00001		
	(-0.08)		
AvMkt%BuyAmt × DumFixCom		-0.23793*	
		(-2.44)	
AvMkt%Commission × DumFixCom			-0.30626***
			(-2.92)
Observations	353,115	299,783	266,297
R-squared	0.19001	0.19151	0.18756
Main Control Variables	Yes	Yes	Yes
House Characteristics	Yes	Yes	Yes
Listing Agent Characteristics	Yes	Yes	Yes

Year/Month/Region FE	Yes	Yes	Yes

Notes: This table repots results from OLS regressions testing the impact of the buying agent's self-interest incentive level on the different binding force of the no-contract constraint under the FPCS. We use the commission rate splits to the buying agents and the fixed amount commission system (FACS) to proxy for the buying agent's self-interest incentive level. Panel A reports coefficients for the model including the commission rate dummy (*DumHighCom*) and its interaction term with *Av#Purchases* (Column 1), *AvMkt%BuyAmt* (Column 2), and *AvMkt%Commission* (Column 3), respectively. Panel B reports coefficients for the model including the FACS dummy (*DumFixCom*) and its interaction term with *Av#Purchases* (Column 1), *AvMkt%BuyAmt* (Column 2), and *AvMkt%Commission* (Column 3), respectively. The dependent variable for all models is the ratio of the final sale price to the last asking price (*SPtoLastAP*). Unreported main controls include *Ln(MOM)*, *#ListingAgents*, *#BuyingAgents*, *#ActiveYrs*, *LABusyness*, *BABusyness*, *DOP*, *ContractDuration*, *DumPriceInc*, *DumPriceDec*, *DumUrban*, *DumDualAgent*, *DumTopBuyingBrokerage*, and *DumTopListingBrokerage*. All columns control for house characteristics, listing agent characteristics, and year, month, and region fixed effects. The estimation sample for all models cover single-family houses in Quebec listed on the MSL during the 2005-2017 period. We report t-values in the parentheses based on standard errors clustered at the FSA and year-month levels. Statistics with significance at 0.5% level are denoted with ***, at 1% level with **, at 5% level with *.

Table 5: Dual-agent Transactions, Intra-office Transactions, and Intra-firm Transactions, 2005-2017

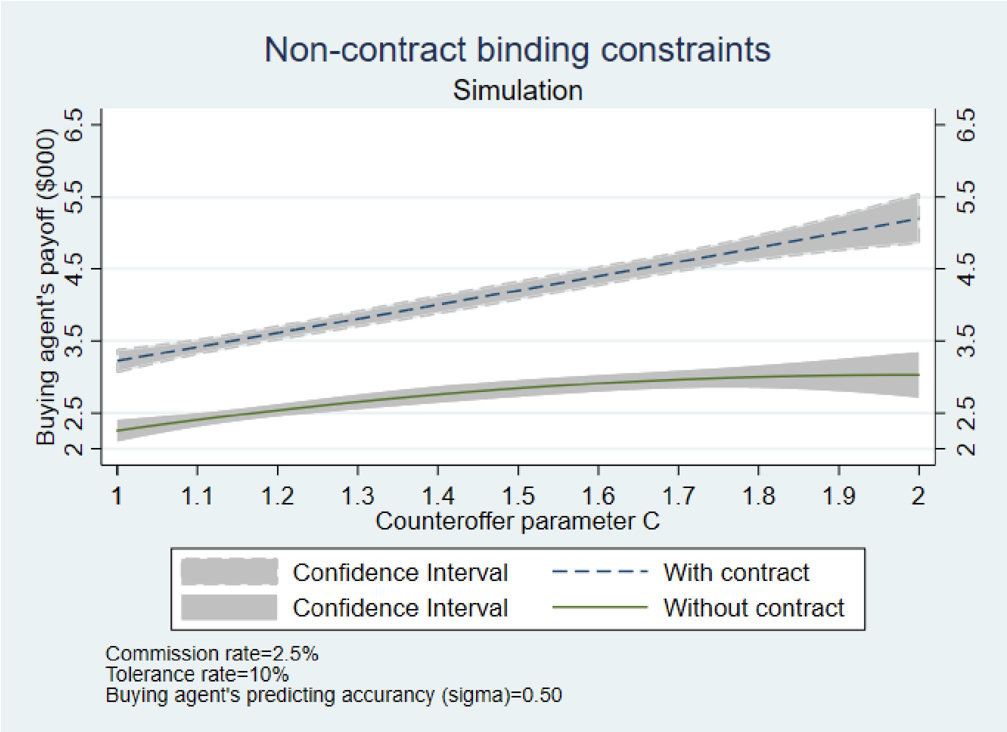
Dependent Variable:	SalePrice/LastAP (SPtoLastAP)		
	(1)	(2)	(3)
Panel A: Intra-office Transactions			
Av#Purchases	0.00012***		
	(4.90)		
AvMkt%BuyAmt		0.07245*	
		(2.54)	
AvMkt%Commission			0.04928*
			(2.02)
DumIntraOffice	-0.00453***	-0.00401***	-0.00403***
	(-9.66)	(-9.97)	(-9.35)
Av#Purchases × DumIntraOffice	0.00009***		
	(3.09)		
AvMkt%BuyAmt × DumIntraOffice		0.13610***	
		(4.53)	
AvMkt%Commission × DumIntraOffice			0.15158***
			(4.54)
Observations	359,122	305,141	270,856
R-squared	0.18807	0.18922	0.18550
Panel B: Intra-firm Transactions			
Av#Purchases	0.00012***		
	(5.00)		
AvMkt%BuyAmt		0.07343*	
		(2.56)	
AvMkt%Commission			0.05062*
			(2.06)
DumIntraFirm	-0.00350***	-0.00337***	-0.00342***
	(-7.47)	(-8.54)	(-8.10)
Av#Purchases × DumIntraFirm	0.00005		
	(1.61)		
AvMkt%BuyAmt × DumIntraFirm		0.10870***	
		(3.46)	
AvMkt%Commission × DumIntraFirm			0.05062*
			(2.06)
Observations	359,122	305,141	270,856
R-squared	0.18796	0.18912	0.18540
Main Control Variables	Yes	Yes	Yes
House Characteristics	Yes	Yes	Yes

Listing Agent Characteristics	Yes	Yes	Yes
Year/Month/Region FE	Yes	Yes	Yes

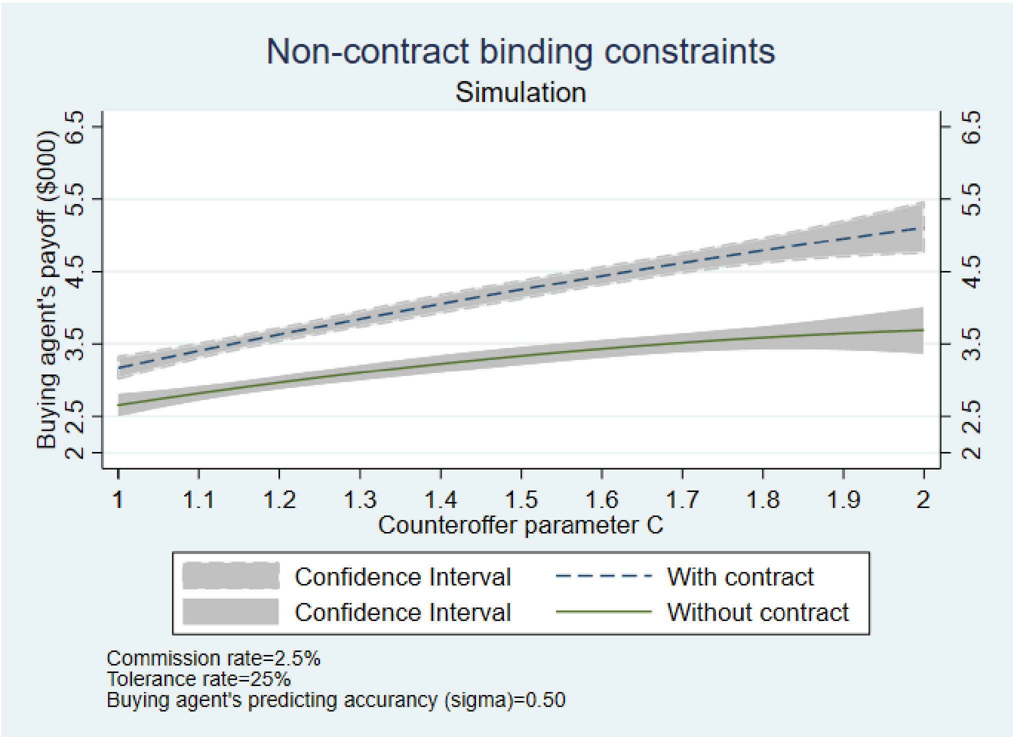
Notes: This table reports results from OLS regressions testing the impact of the collusion opportunities with listing agents on the different binding force of the no-contract constraint under the FPCS. We use intra-office transactions and intra-firm transactions to proxy for the collusion opportunities of buying agents with listing agents. Panel A reports coefficients for the model including the intra-office transaction dummy (*DumIntraOffice*) and its interaction term with *Av#Purchases* (Column 1), *AvMkt%BuyAmt* (Column 2), and *AvMkt%Commission* (Column 3), respectively. Panel B reports coefficients for the model including the intra-firm transaction dummy (*DumIntraFirm*) and its interaction terms with *Av#Purchases* (Column 1), *AvMkt%BuyAmt* (Column 2), and *AvMkt%Commission* (Column 3), respectively. The dependent variable for all models is the ratio of the final sale price to the last asking price (*SPtoLastAP*). Unreported main controls include *DumDualAgent*, *Ln(MOM)*, *#ListingAgents*, *#BuyingAgents*, *#ActiveYrs*, *LABusyness*, *BABusyness*, *DOP*, *ContractDuration*, *DumPriceInc*, *DumPriceDec*, *DumUrban*, *DumTopBuyingBrokerage*, and *DumTopListingBrokerage*. All columns control for house characteristics, listing agent characteristics, and year, month, and region fixed effects. The estimation sample covers single-family houses in the Quebec listed on the MLS during the 2005-2017 period. We report t-values in the parentheses based on standard errors clustered at the FSA and year-month levels. Statistics with significance at 0.5% level are denoted with ***, at 1% level with **, at 5% level with *.

Figure 1 – Simulation Results

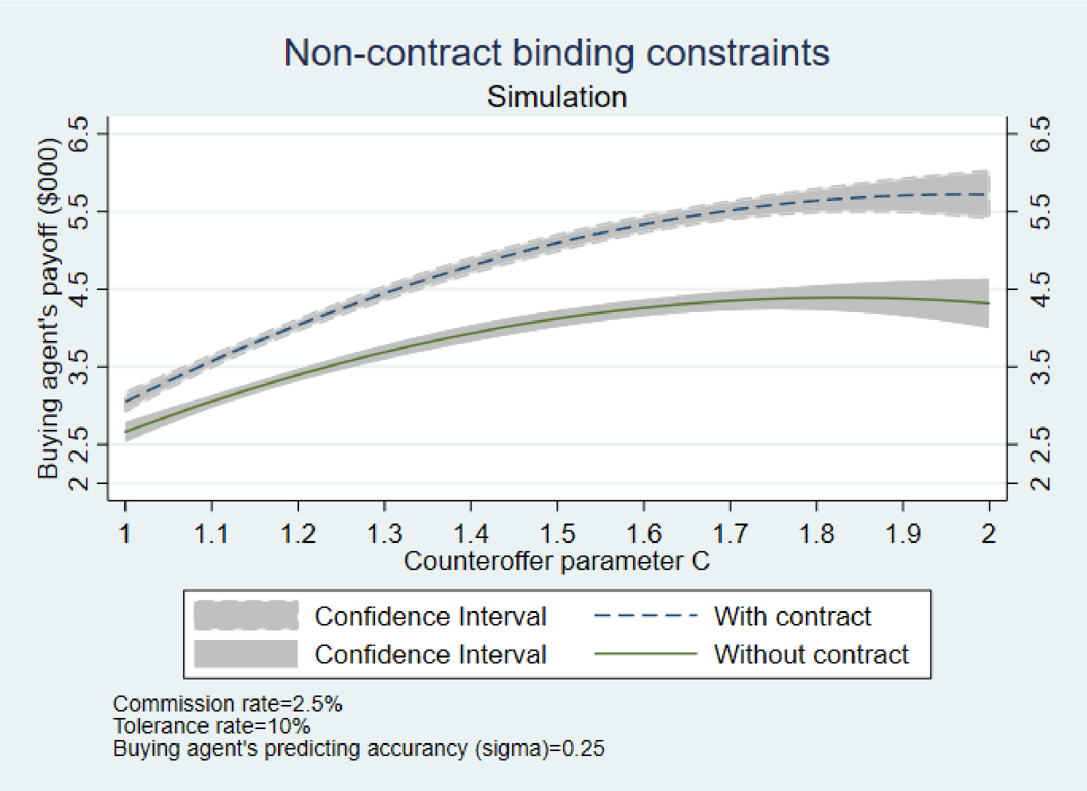
Panel A: Quadratic Plot of the Base Case



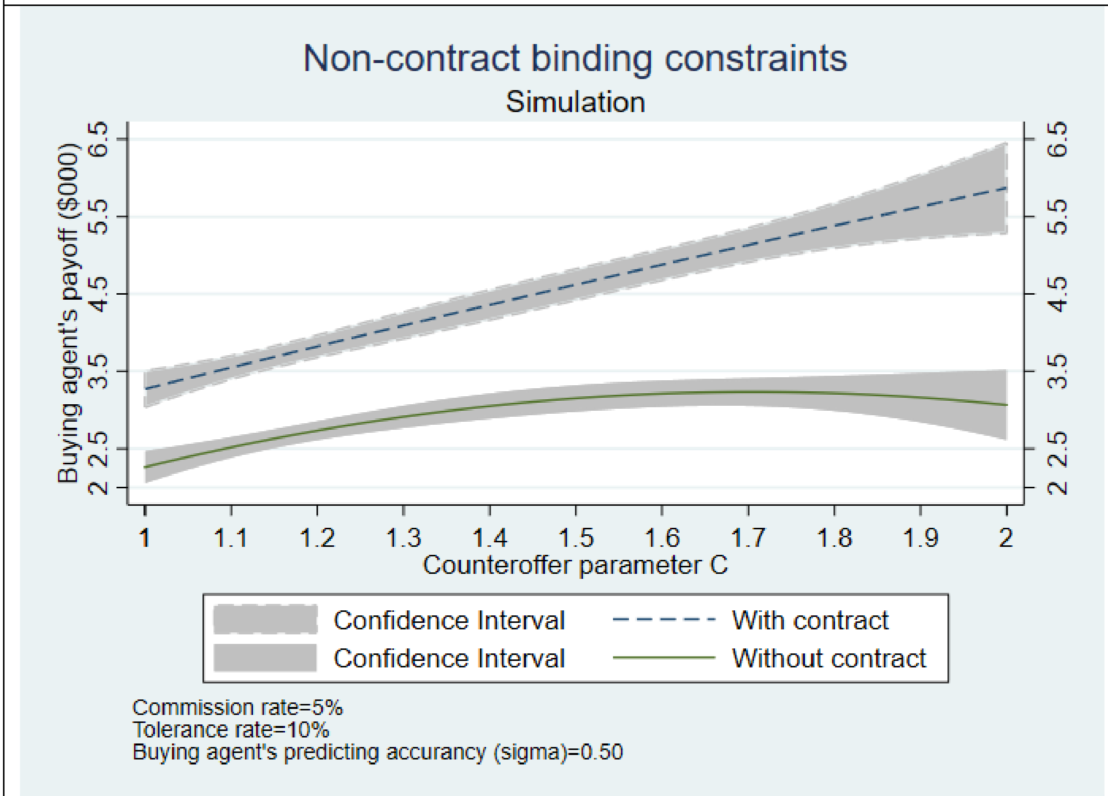
Panel B: Quadratic Plot of the Tolerance Version



Panel C: Quadratic Plot of the Accuracy Version



Panel D: Quadratic Plot of the Commission Version



Appendix 1 Variable Definitions

Variables	Definitions
Panel A: Outcome Variables	
SPtoOriginalAP	Sale price to original asking price ratio
SPtoLastAP	Sale price to last asking price ratio
DumSold	Sold dummy (=1, if the house being sold; =0, if the house being expired)
SP	Sale price
Ln(SP)	Log of sale price
OriginalAP	Original asking price
Ln(OAP)	Log of original asking price
LastAP	Last asking price
Ln(LAP)	Log of last asking price
Panel B: Testing Variables	
Av#Purchases	Annual average # of transactions the buying agent involved as a buying agent in the prior 5 years.
AvMkt%BuyAmt	Annual average market share of the buying agent based on purchase amount in the same region in the prior 5 years.
AvMKT%Commission	Annual average market share of the buying agent based on commission earned in the same region in the prior 5 years
Av#Transactions	Annual average # of transactions the buying agent involved as a listing agent in the prior 5 years.
Av%SuccessSales	Annual average % of successful transactions the buying agent involved as a listing agent in the prior 5 years.
Panel C: Main Control Variables	
PredSalePrice	Predicted value of the log sale price from Heckman Selection model
MOM	Listing months on the market before the house being sold or being expired
Ln(MOM)	Log of MOM
DOM	Listing days on the market before the houses being sold
Ln(DOM)	Log of DOM
#ListingAgents	# of listing agents involved in the transaction
#BuyingAgents	# of buying agents involved in the transaction
#ActiveYrs	# of buying agents' active years
LABusyness	Listing agent busyness: total # of listings the listing agent involved during the contract period
BABusyness	Buying agent busyness: total # of listings the first buying agent involved during the period between the house being sold and 180 days after the house being sold
DOP	Degree of overpricing (Anglin, 2003 and Rutherford, 2005
ContractDuration	Duration of the selling contract between sellers and their listing agents
DumPriceInc	Asking price increase dummy (=1, if LastAP > OriginalAP; =0, otherwise)
DumPriceDec	Asking price decrease dummy (=1, if LastAP < OriginalAP; =0, otherwise)

DumUrban	Urban location dummy (=1, if houses locate in the urban area; =0, otherwise)
DumDualAgent	Dual agent transaction dummy (=1, if transaction has dual agents; =0, otherwise)
DumTopBuyingBrokerage	Top buying brokerage firm dummy (=1, if the buying agent attached to the top 6 brokerage firm; =0, otherwise)
DumTopListingBrokerage	Top listing brokerage firm dummy (=1, if the listing agent attached to the top 6 brokerage firm; =0, otherwise)
Panel D: Other Important Variables	
DumATYP	Atypical house dummy (=1, if the house's Atypicality index is in the top 5 percentile in its region in that year; =0, otherwise)
DumHighValue	High-value house dummy (=1, if the house's predicted value is in the top 5 percentile of its region in that year; =0, otherwise)
Dum1stListing	First listing dummy (=1, if the house never has been listed on the MLS in the prior 10 years; =0, otherwise)
DumOldAge	Old-age house dummy (=1, if the house's construction age is in the top 5 percentile of its region in that year; =0, otherwise)
DumHighCom	High commission rate dummy (=1, if the commission rate splits to the buying agent > 2.5%; =0, otherwise)
DumFixCom	Fix amount commission dummy (=1, if the fix amount commission splits to the buying agent; =0, otherwise)
DumIntraOffice	Intra office transaction dummy (=1, if the listing agent and the buying agent of the transaction are from the same office; =0, otherwise)
DumIntraFirm	Intra firm transaction dummy (=1, if the listing agent and the buying agent of the transaction are from the same firm; =0, otherwise)
ListingDensity	Listing density variable: measures average competing houses on the market on each listing day
Competition	Competition variable: measures cumulative competition from other houses listed on the market (in listing days) during the listing period
AvPastSPtoLAPBA	Exponential weighted average SPtoLastAP of the buying agent as buying agents in prior 5 years.
AvPastSPtoLAPLA	Exponential weighted average SPtoLastAP of the buying agent as listing agents in prior 5 years.

Notes: This table reports summary statistics for house characteristics, our main testing variables: *Buying Agent Heterogeneity*, dependent variables: *Transaction Outcomes*, and main control variables.

Conflicts of Interest and Agent Heterogeneity in Buyer Brokerage

Online Supplementary Appendix (OSA)

This OSA provides all the material (tables, figures, model extensions, etc.) that are referred to in the main text. The OSA will be available online and is made available to the referee(s) during the review process.

Online Supplementary Appendix 1 (OSA 1) – Example of Buyer Representative Agreement (BRA) in North American

Province or State	**Buyer’s broker or Seller’s broker (Sub-agent)**	**BRA mandatory?**	**Buyer’s walk away cost**
Panel A: Canada			
Alberta	Buyer’s broker (client)	Effective July 1, 2014, Buyer Representation Agreements (BRAs) become mandatory in Alberta.	Costly: If you have signed an exclusive agreement and chose to work with other agents, you are at risk of owing more than one agent a commission when you decide to buy.
British Columbia		No, BRA is not common in residential transactions, but it is growing	Holdover clause
Manitoba	Buyer’s broker (Assumed Buyer Agency)	Not required between buyer and buyer's agency, but permissible	Free
Nova Scotia		As of January 1, 2017, the Nova Scotia Real Estate Commission requires that all buyers who agree to be clients of a real estate brokerage firm must sign a BRA in Nova Scotia.	Similar situation as in Alberta
Ontario	Buyer’s broker	Mandatory for client. Salespeople have a written BRA presented for signature prior to an offer being presented on behalf of the Buyer. If no agreement signed, the buyer is a customer	Not free but easy steps to cancel the BRA
Quebec	Buyer’s broker	Not mandatory but recommended.	Free.

Panel B: United States			
California	Buyer's broker (NAP-11 & AAP-11)	Not required by law but recommended.	BR-11: revocable NAP-11 & AAP-11: non-revocable.
Colorado	Buyer's broker (written agreement) Transaction broker (no written agreement)	Mandatory, otherwise there is no agency relationship between broker and buyer. Broker acts as a transaction broker.	Costly: An agency contract can be terminated by 1. mutual agreement, 2. revocation by the principal, 3. death of either party. An agency contract may be terminated although the party that is terminating the contract may be held liable for doing so.
Connecticut	Buyer's broker (written agreement) Sub-agent (no agreement and seller's written permission)	Mandatory, otherwise, the agent is the sub-agent (with seller's written permission).	Bound relationship and costly to walk away.
Florida	Buyer's broker (with BRA) Transaction broker (without BRA)	Not mandatory.	
Illinois	Buyer's broker (written or implied)	Disclosure of Buyer/Tenant Designated Agent form is required in Illinois (effective in Jan 2010) to acknowledge the receipt, but neither non-exclusive but paying commission agreement nor exclusive buyer representation agreement is mandatory.	Exclusive-BRA can be cancelled by the buyer with reasons. If the agent refuses to cancel, the client can go through the broker to cancel the agency relationship. For other relationship, it is easy and costless to walk away.
Indiana	Sub-agency prohibited	No	
Texas	Buyer's broker (a relationship between a broker and a client can legally exist without a written document.)	Not mandatory. A buyer can choose the broker with whom the buyer wants to work. Buyer representative agreement is a binding contract with broker, not individual salesperson.	No BRA: free. BRA is a binding contract, and it is costly to walk away.
Utah		A written agency agreement between a buyer and the individual represents are required for the purpose of defining the scope of the individual's agency.	

Online Supplementary Appendix 2 (OSA 2)

OSA 2.1 Two-stage TILI Negotiation

There are four possible outcomes in the two-stage TILI negotiation:

Case 1: If $R_i^B \geq p_i^a$, the buyer accepts the asking price and purchases the house with a final sale price of $p_i = p_i^a$. The associated probability is $prob(Case1) = (1-n)$. **(Outcome 1)**

Case 2: If $R_i^B < p_i^a$, the buyer rejects the asking price and proposes an offer of p_i^c based on the suggestion of the buying agent.

Case 2a: If $R_i^S \leq p_i^c$, the seller accepts p_i^c and sells the house with a final sale price of $p_i = p_i^c$. The associated probability is $prob(Case2a) = n(1-w)$. **(Outcome 2)**

Case 2b: If $R_i^S > p_i^c$, the seller rejects p_i^c and proposes a counteroffer of p_i^f.

Case 2b1: If $R_i^B \geq p_i^f$, the buyer accepts p_i^f and purchases the house with a final sale price of $p_i = p_i^f$. The associated probability is $prob(Case2a1) = nw(1-r)$. **(Outcome 3)**

Case 2b2: If $R_i^B < p_i^f$, the buyer rejects p_i^f and the negotiation is ended without a deal. The associated probability is $prob(Case2a2) = nwr$. **(Outcome 4)**

OSA 2.1.1 Without a Binding Contract between the Buyer and the Buying Agent

After introducing the additional negotiating stage, the final sale price of the house i, p_i, ,in the two-stage counterpart of equation (2) is:

$$p_i = (1-n)p_i^a + n(1-w)p_i^c + nw(1-r)p_i^f$$

$$\widehat{R_i^S} \leq p_i^c \leq R_i^B;$$

$$R_i^S \leq p_i^f \leq \widehat{R_i^B} \tag{A1}$$

The buyer's payoff in the two-stage counterpart of equation (4) is:

$$\pi_B = R_i^B - (1-n)p_i^a - n\left[1 - \Phi\left(\frac{-lnc}{\sigma^S}\right)\right]c\widehat{R_i^S} - kt$$

$$1 \leq c \leq \frac{R_i^B}{\widehat{R_i^S}} \tag{A2}$$

Then the two-stage counterpart of equation (5) is:

$$\frac{\partial \pi_B}{\partial c} = -n\widehat{R_i^S}\left[1 - \Phi\left(\frac{-lnc}{\sigma^S}\right) + \frac{1}{\sigma^S}\phi\left(\frac{-lnc}{\sigma^S}\right)\right] + n(1-r)p_i^f\frac{1}{\sigma^S c}\phi\left(\frac{-lnc}{\sigma^S}\right) \qquad \text{(A3)}$$

We find that after adding a positive term into the one-stage TILI model equation (5), its two-stage TILI model counterpart given by equation (A3) is greater.

The buying agent's payoff in the two-stage counterpart of equation (7) is:

$$\pi_{sa} = \alpha\left\{(1-n)p_i^a + n\left[1 - \Phi\left(\frac{-lnc}{\sigma^S}\right)\right]c\widehat{R_i^S}\right\} - F$$

$$1 \le c \le \frac{\widehat{R_i^B}}{\widehat{R_i^S}} \qquad \text{(A4)}$$

Then the two-stage counterpart of equation (8) is:

$$\frac{\partial \pi_{sa}}{\partial c} = \alpha n\widehat{R_i^S}\left[1 - \Phi\left(\frac{-lnc}{\sigma^S}\right) + \frac{1}{\sigma^S}\phi\left(\frac{-lnc}{\sigma^S}\right)\right] - \alpha n(1-r)p_i^f\frac{1}{\sigma^S c}\phi\left(\frac{-lnc}{\sigma^S}\right) \qquad \text{(A5)}$$

We find that after adding a negative term into the one-stage TILI model equation (8), its two-stage TILI model counterpart given by equation (A5) is smaller.

OSA 2.1.2 With a Binding Contract between the Buyer and the Buying Agent

After introducing the additional negotiating stage, the final sale price of the house i, $p_i{}'$, in the two-stage counterpart of equation (10) is:

$$p_i{}' = (1-n)p_i^a + n(1-v)(1-w)p_i^c + n(1-v)w(1-r)p_i^f$$

$$\widehat{R_i^S} \le p_i^c \le \widehat{R_i^B};$$

$$R_i^S \le p_i^f \le \widehat{R_i^B} \qquad \text{(A6)}$$

The buyer's payoff in the case without a binding contract between buyers and buying agents is the same as that in the case with a binding contract because the buyer bears a negligible cost of switching to other buying agents. Thus, the buying agent's payoff in the two-stage counterpart of equation (12) is:

$$\pi_{sa}{}' = \alpha\left\{(1-n)p_i^a + n[1-\Phi(Y)][1-\Phi(X)]h\widehat{R_i^B}\right\} + \alpha n(1-r)p_i^f\Phi(X)[1-\Phi(Y)]$$

$$\frac{\widehat{R_i^S}}{\widehat{R_i^B}} \le h \le 1 \qquad \text{(A7)}$$

X and Y are previously defined: $X = \frac{-ln\left(h\frac{\widehat{R_i^B}}{\widehat{R_i^S}}\right)}{\sigma^S}$ and $Y = \frac{ln(hR_i^B)-ln(R_i^B+\varphi_j)}{\sigma^B}$.

Then the two-stage counterpart of equation (13) is:

$$\frac{\partial \pi_{sa}{}'}{\partial h} = \alpha n\widehat{R_i^B}\,[1-\Phi(Y)][1-\Phi(X)] - \frac{\alpha n\widehat{R_i^B}}{\sigma^B}\phi(Y)[1-\Phi(X)] + \frac{\alpha n\widehat{R_i^B}}{\sigma^S}\phi(X)[1-\Phi(Y)]$$

$$-\alpha n(1-r)p_i^f\left\{\frac{1}{\sigma^S h}\phi(X)[1-\Phi(Y)] + \frac{1}{\sigma^B h}\Phi(X)\phi(Y)\right\} \qquad (A8)$$

We find that after adding a negative term into the one-stage TILI model equation (13), its two-stage TILI model counterpart given by equation (A8) is smaller.

OSA 2.2 Multi-stage TILI Negotiation

We denote l as the number of offers proposed by each buyer and seller. In the multi-stage TILI negotiation, the negotiation ends without a deal if the buyer rejects the l^{th} offer, ${}^{l}p_i^f$. We name the l^{th} offer, ${}^{l}p_i^f$, which is proposed by the seller, as the take-it-or-leave it offer in the multi-stage TILI negotiation. There are $2l+2$ possible outcomes in the multi-stage TILI negotiation:

Case 1: If $R_i^B \geq p_i^a$, the buyer accepts the asking price and purchases the house with a final sale price of $p_i = p_i^a$. The associated probability is $prob(Case1) = (1-n)$. **(Outcome 1)**

Case 2: If $R_i^B < p_i^a$, the buyer rejects the asking price and proposes an offer of ${}^{1}p_i^c$ based on the advice of the buying agent.

Case 2a: If $R_i^S \leq {}^{1}p_i^c$, the seller accepts ${}^{1}p_i^c$ and sells the house with a final sale price of $p_i = {}^{1}p_i^c$. The associated probability is $prob(Case2a) = n(1-w_1)$. **(Outcome 2)**

Case 2b: If $R_i^S > {}^{1}p_i^c$, the seller rejects ${}^{1}p_i^c$ and proposes a new counteroffer of ${}^{1}p_i^f$.

Case 2b1: If $R_i^B \geq {}^{1}p_i^f$, the buyer accepts ${}^{1}p_i^f$ and purchases the house with a final sale price of $p_i = {}^{1}p_i^f$. The associated probability is $prob(Case2a1) = nw_1(1-r_1)$. **(Outcome 3)**

Case 2b2: If $R_i^B < {}^{1}p_i^f$, the buyer rejects ${}^{1}p_i^f$ and proposes a counteroffer of ${}^{2}p_i^c$.

Case 2b2a: If $R_i^S \leq {}^{2}p_i^c$, the seller accepts ${}^{2}p_i^c$ and sells the house with a final sale price of $p_i = {}^{2}p_i^c$. The associated probability is $prob(Case2b2a) = nw_1r_1(1-w_2)$. **(Outcome 4)**

Case 2b2b: If $R_i^S > {}^{2}p_i^c$, the seller rejects ${}^{2}p_i^c$ and proposes a new counteroffer of ${}^{2}p_i^f$.

Case2b2b1: If $R_i^B \geq {}^2p_i^f$, the buyer accepts ${}^2p_i^f$ and purchases the house with a final sale price of $p_i = {}^2p_i^f$. The associated probability is $prob(Case2a2b1) = nw_1r_1w_2(1-r_2)$. **(Outcome 5)**

Case 2b2b2: If $R_i^B < {}^2p_i^f$, the buyer rejects ${}^2p_i^f$ and proposes another new counteroffer of ${}^3p_i^c$.

$\vdots$

Case 2b2b…2a: If $R_i^S \leq {}^lp_i^c$, the seller accepts the previous counteroffer, denoted as ${}^lp_i^c$ and sells the house with a final sale price of $p_i = {}^lp_i^c$. The associated probability is $prob(Case2b2b \ldots 2a) = nw_1r_1w_2r_2 \ldots w_{l-1}r_{l-1}(1-w_l)$. **(Outcome 2*l*)**

Case 2b2b…2b: If $R_i^S > {}^lp_i^c$, the seller rejects ${}^lp_i^c$ and proposes a new counteroffer of ${}^lp_i^f$.

Case 2b2b…2b1: If $R_i^B \geq {}^lp_i^f$, the buyer accepts ${}^lp_i^f$ and purchases the house with a final sale price of $p_i = {}^lp_i^f$. The associated probability is $prob(Case\ 2b2b \ldots 2b1) = nw_1r_1w_2r_2 \ldots w_{l-1}r_{l-1}w_l(1-r_l)$. **(Outcome 2*l*+1)**

Case 2b2b…2b2: If $R_i^B < {}^lp_i^f$, the buyer rejects ${}^lp_i^f$ and the negotiation is ended without a deal. The associated probability is $prob(Case\ 2b2b \ldots 2b2) = nw_1r_1w_2r_2 \ldots w_{l-1}r_{l-1}w_lr_l$. **(Outcome 2*l*+2)**

OSA 2.2.1 Without a Binding contract between the Buyers and the Buying Agent

After introducing the additional negotiating stages, the final sale price of house i, p_i, in the multi-stage counterpart of equation (2) is:

$$p_i = (1-n)p_i^a + n(1-w_1)\,{}^1p_i^c + nw_1(1-r_1)\,{}^1p_i^f$$

$$+ \cdots + nw_1r_1w_2r_2 \ldots w_{l-1}r_{l-1}(1-w_l)\,{}^lp_i^c$$

$$+ nw_1r_1w_2r_2 \ldots w_{l-1}r_{l-1}w_l(1-r_l)\,{}^lp_i^f$$

$$\widehat{R_i^S} \leq {}^lp_i^c \leq R_i^B;$$

$$R_i^S \leq {}^lp_i^f \leq \widehat{R_i^B} \quad for\ all\ l = 1, 2, \ldots, l \tag{A9}$$

We assume a constant value c_l that makes ${}^{l}p_i^c = c_l\widehat{R_i^S}$, and $1 \le c_l \le \frac{R_i^B}{\widehat{R_i^S}}$. Thus, c_1 is the c in the one-stage and the two-stage negotiations. To compare the multi-stage negotiation with the one-stage and the two-stage negotiations, we focus on the buyer's choice on the first offer price ${}^{1}p_i^c$ or c_1.

Then, $w_1 = \Phi\left(\frac{-lnc_1}{\sigma^S}\right)$, ${}^{1}p_i^c = c_1\widehat{R_i^S}$ and the buyer's payoff in the multi-stage counterpart of equation (4) is:

$$\pi_B = R_i^B - (1-n)p_i^a - n\left[1 - \Phi\left(\frac{-lnc_1}{\sigma^S}\right)\right]c_1\widehat{R_i^S} - n(1-r_1)^1p_i^f\Phi(w_1)$$

$$- \cdots - nr_1w_2r_2 \ldots w_{l-1}r_{l-1}(1-w_l)^lp_i^c\Phi(w_1)$$

$$-nr_1w_2r_2 \ldots w_{l-1}r_{l-1}w_l(1-r_l)^lp_i^f\Phi(w_1) - kt$$

$$1 \le c_1 \le \frac{R_i^B}{\widehat{R_i^S}} \tag{A10}$$

To simplify the presentation of the above results, we define $c_1(*) = \frac{1}{\sigma^S c_1}\phi\left(\frac{-lnc_1}{\sigma^S}\right) > 0$.

Then the multi-stage counterpart of equation (5) is:

$$\frac{\partial \pi_B}{\partial c_1} = -n\widehat{R_i^S}\left[1 - \Phi\left(\frac{-lnc_1}{\sigma^S}\right) + \frac{1}{\sigma^S}\phi\left(\frac{-lnc_1}{\sigma^S}\right)\right] + n(1-r_1)^1p_i^f c_1(*)$$

$$+ \cdots + nr_1w_2r_2 \ldots w_{l-1}r_{l-1}(1-w_l)^lp_i^c c_1(*)$$

$$+nr_1w_2r_2 \ldots w_{l-1}r_{l-1}w_l(1-r_l)^lp_i^f c_1(*) \tag{A11}$$

We find that after adding positive terms into the one-stage TILI model equation (5), and the two-stage TILI model equation (A3), its multi-stage TILI model counterpart given by equation (A11) is greater. We summarize that $\frac{\partial \pi_B}{\partial c_1}(\text{multi} - \text{stage}) > \frac{\partial \pi_B}{\partial c_1}(two - stage) > \frac{\partial \pi_B}{\partial c_1}(one - stage)$.

The buying agent's payoff in the multi-stage counterpart of equation (7) is:

$$\pi_{sa} = \alpha\left\{(1-n)p_i^a + n\left[1 - \Phi\left(\frac{-lnc_1}{\sigma^S}\right)\right]c\widehat{R_i^S}\right.$$

$$+ n(1-r_1)^1p_i^f\Phi(w_1) + \ldots + nr_1w_2r_2 \ldots w_{l-1}r_{l-1}(1-w_l)^lp_i^c\Phi(w_1)$$

$$\left.+ nr_1w_2r_2 \ldots w_{l-1}r_{l-1}w_l(1-r_l)^lp_i^f\Phi(w_1)\right\} - F$$

$$1 \le c_1 \le \frac{\widehat{R_i^B}}{\widehat{R_i^S}} \tag{A12}$$

Then, the multi-stage counterpart of equation (8) is:

$$\frac{\partial \pi_{sa}}{\partial c_1} = \alpha n\widehat{R_i^S}\left[1 - \Phi\left(\frac{-lnc_1}{\sigma^S}\right) + \frac{1}{\sigma^S}\phi\left(\frac{-lnc_1}{\sigma^S}\right)\right] - \alpha n(1-r)^1 p_i^f c_1(*)$$

$$- \cdots - \alpha n r_1 w_2 r_2 \ldots w_{l-1} r_{l-1}(1-w_l)^l p_i^c c_1(*)$$

$$-\alpha n r_1 w_2 r_2 \ldots w_{l-1} r_{l-1} w_l (1-r_l)^l p_i^f c_1(*) \tag{A13}$$

We find that after adding negative terms into the one-stage TILI model equation (8), and the two-stage TILI model equation (A5), its multi-stage TILI model counterpart given by equation (A13) is smaller. We summarize that $\frac{\partial \pi_{sa}}{\partial c_1}(\text{multi} - \text{stage}) < \frac{\partial \pi_{sa}}{\partial c_1}(two - stage) < \frac{\partial \pi_{sa}}{\partial c_1}(one - stage)$.

OSA 2.2.2 With a Binding Contract between the Buyers and the Buying Agent

After introducing the multiple stage of negotiations, the final sale price of house i, p_i', in the multi-stage counterpart of equation (10) is:

$$p_i' = (1-n)p_i^a + n(1-v_1)(1-w_1)^1 p_i^c + n(1-v_1)w_1(1-r_1)^1 p_i^f$$

$$+ \cdots + n(1-v_1)(1-v_2)\ldots(1-v_l)w_1 r_1 w_2 r_2 \ldots w_{l-1} r_{l-1}(1-w_l)^l p_i^c$$

$$+n(1-v_1)(1-v_2)\ldots(1-v_l)w_1 r_1 w_2 r_2 \ldots w_{l-1} r_{l-1} w_l (1-v_l)^l p_i^f$$

$$\widehat{R_i^S} \le {}^l p_i^c \le \widehat{R_i^B};$$

$$R_i^S \le {}^l p_i^f \le \widehat{R_i^B} \;\; for\, all\, l = 1,2,\ldots,l \tag{A14}$$

The buyer’s payoff in the case without a binding contract between buyers and buying agents is the same as that in the case with a binding contract because the buyers bear a negligible cost of switching to other buying agents.

We assume a constant value h_l that makes ${}^l p_i^c = h_l \widehat{R_i^B}$, and $\frac{\widehat{R_i^S}}{\widehat{R_i^B}} \le h_l \le 1$. Thus, h_1 is the h in the one-stage and the two-stage negotiations. To compare the multi-stage negotiation with the one-stage and the two-stage negotiations, we focus on the buyer’s choice on the first offer price ${}^1 p_i^c$ or h_1.

Since ${}^1 p_i^c = h_1 \widehat{R_i^B} = c_1 \widehat{R_i^S}$, $c_1 = h_1 \frac{\widehat{R_i^B}}{\widehat{R_i^S}}$ and $v_1 = prob({}^l p_i^c > R_i^B + \varphi_j) =$ $\Phi\left[\frac{ln(h_1 R_i^B) - ln(R_i^B + \varphi_j)}{\sigma^B}\right]$.

Buying agent’s payoff in the multi-stage counterpart of equation (12) is:

$$\pi_{sa}{}' = \alpha\left\{(1-n)p_i^a + n[1-\Phi(Y)][1-\Phi(X)]h_1\widehat{R_i^B}\right\}$$

$$+\left\{\alpha n(1-r_1)^1 p_i^f + \cdots + \alpha n(1-v_2)\ldots(1-v_l)r_1w_2r_2\ldots w_{l-1}v_{l-1}(1-w_l)^l p_i^c\right.$$

$$\left.+\,\alpha n(1-v_2)\ldots(1-v_l)r_1w_2r_2\ldots w_{l-1}v_{l-1}w_l(1-v_l)^l p_i^f\right\}\{\Phi(X)[1-\Phi(Y)]\}$$

$$\frac{\widehat{R_i^S}}{\widehat{R_i^B}} \le h_1 \le 1 \tag{A15}$$

X and Y are previously defined: $X = \frac{-ln\left(h_1\frac{\widehat{R_i^B}}{\widehat{R_i^S}}\right)}{\sigma^S}$ and $Y = \frac{ln(h_1R_i^B)-ln(R_i^B+\varphi_j)}{\sigma^B}$.

Then, the multi-stage counterpart of equation (13) is:

$$\frac{\partial\pi_{sa}{}'}{\partial h_1} = \alpha n\widehat{R_i^B}\,[1-\Phi(Y)][1-\Phi(X)] - \frac{\alpha n\widehat{R_i^B}}{\sigma^B}\phi(Y)[1-\Phi(X)] + \frac{\alpha n\widehat{R_i^B}}{\sigma^S}\phi(X)[1-\Phi(Y)]$$

$$-\left\{\alpha n(1-r_1)^1 p_i^f + \cdots + \alpha n(1-v_2)\ldots(1-v_l)r_1w_2v_2\ldots w_{l-1}v_{l-1}(1-w_l)^l p_i^c\right.$$

$$\left.+\,\alpha n(1-v_2)\ldots(1-v_l)r_1w_2v_2\ldots w_{l-1}v_{l-1}w_l(1-v_l)^l p_i^f\right\}$$

$$\times\left\{\frac{1}{\sigma^S h_1}\phi(X)[1-\Phi(Y)] + \frac{1}{\sigma^B h_1}\Phi(X)\phi(Y)\right\} \tag{A16}$$

We find that after adding negative terms into the one-stage TILI model equation (13), and the two-stage TILI model equation (A8), its multi-stage TILI model counterpart given by equation (A16) is smaller. We summarize that $\frac{\partial\pi_{sa}}{\partial h_1}(\text{multi}-\text{stage}) < \frac{\partial\pi_{sa}}{\partial h_1}(two-stage) < \frac{\partial\pi_{sa}}{\partial h_1}(one-stage)$.

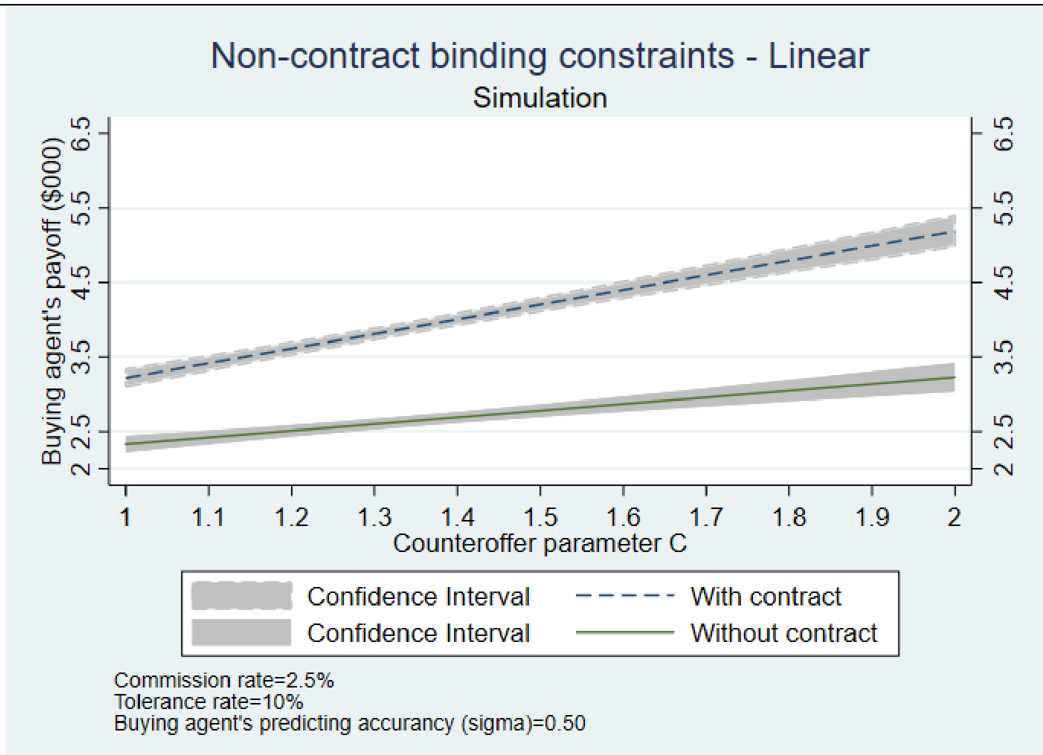
In sum, introducing more negotiating stages and giving both sellers and buyers more opportunities to negotiate (increase the number of l) increases the probability of interest alignments between buying agents and buyers.

Proposition A1: Additional rounds in the negotiation increase the probability of interest alignments between buying agents and buyers, and thereby increase the efficiency of the fixed percentage commission system (FPCS).

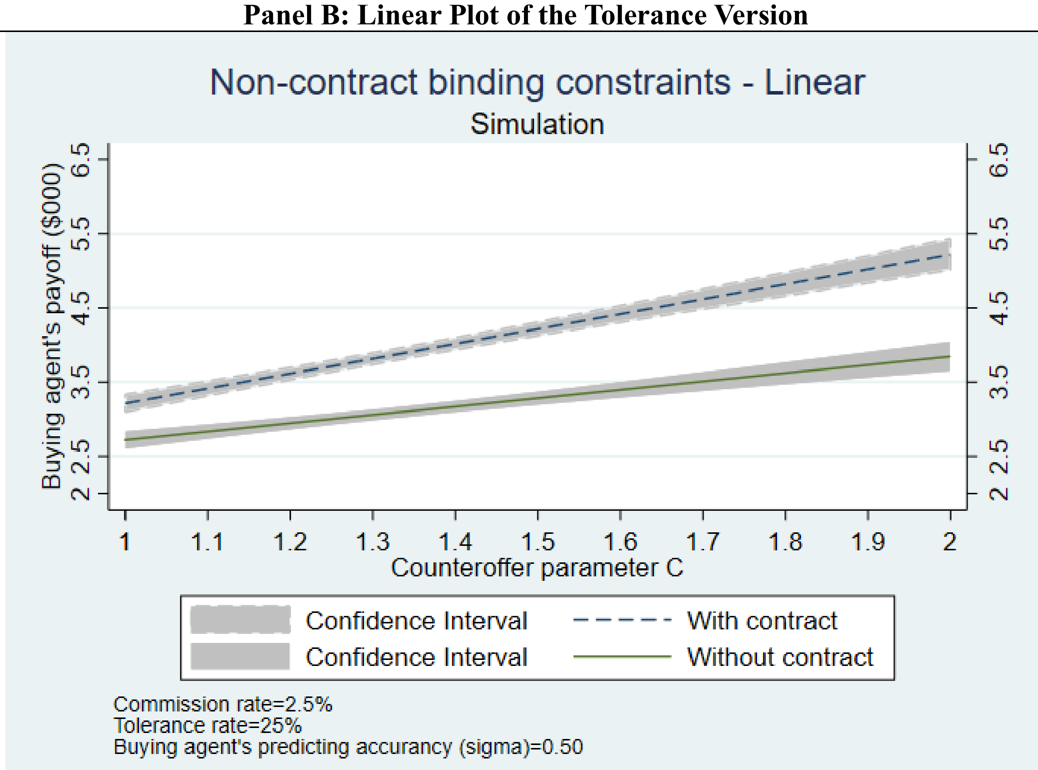
Proposition A2: Additional rounds in the negotiation decrease the buying agent's incentive of being self-interested.

Online Supplementary Appendix 3 (OSA 3) – Simulation Results (Linear plot)

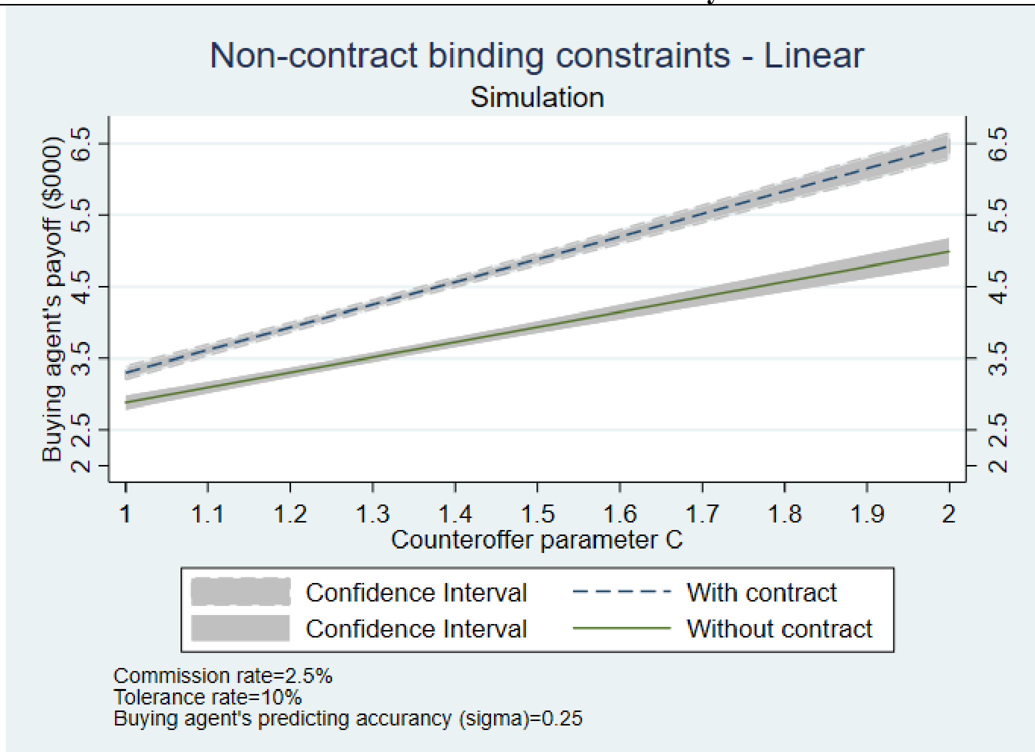
Panel A: Linear Plot of the Base Case



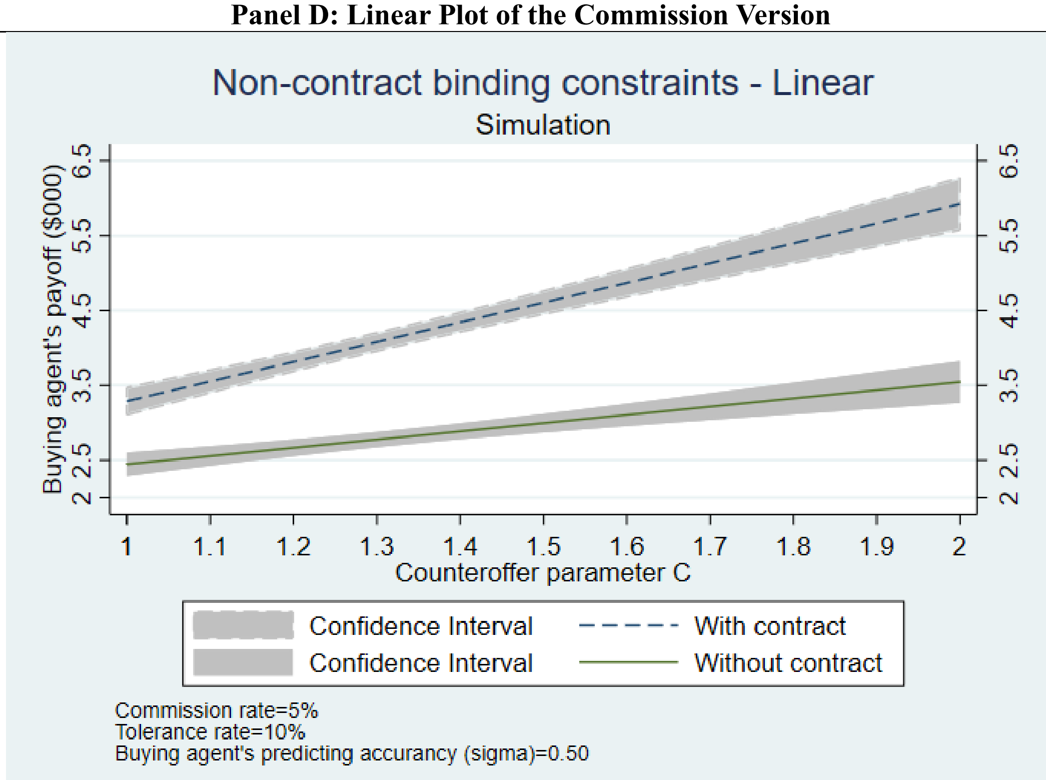
Panel B: Linear Plot of the Tolerance Version



Panel C: Linear Plot of the Accuracy Case



Panel D: Linear Plot of the Commission Version



Online Supplementary Appendix 4 (OSA 4)

OSA 4. Predicted Selling and Asking Prices for a House

We estimate the predicted selling price of house i, $\hat{P}_i^s$, based on its characteristics X_i under the market conditions for a certain forward sortation area (FSA) based on the first three digits of the Canadian postal code in a given month and year when the house gets sold or a listing expires, whichever comes first. We use a two-step Heckman Selection model (Heckman, 1979) because final sale prices are missing for expired properties and Ordinary Least Square (OLS) estimations would be biased due to the incidental truncation of the sample. We calculate the inverse Mill ratio (IMR) using the output from a first-step Probit model used to estimate the probability of a house being sold by taking the ratio of the probability density function (PDF) to the cumulative distribution function (CDF) of the distribution. In the second and final step, we regress the final sale price on the house's characteristics, market conditions, and the IMR. Since the estimated coefficients from the hedonic OLS and the Heckman selection models are similar, the predicted values from the Heckman selection model are used in the following sections of the paper.

The two equations in the Heckman selection model are:

$$DumSold = \alpha_0 + \sum \alpha_i X_i + F_{Year} + F_{Month} + F_{FSA} + \epsilon_i \tag{A17}$$

$$ln(P_i^S) = \beta_0 + \beta_1 \lambda_i + \sum \beta_i X_i + F_{Year} + F_{Month} + F_{FSA} + \varepsilon_i \tag{$A18$}$$

where $DumSold$ is a binary outcome variable, which equals one if the house is sold and zero if the house is expired. λ_i is the IMR from the probit model (E1). $ln(P_i^s)$ represents the natural log of the final sale price, and the X_is are the characteristics of house i. F_{Year}, F_{Month}, and F_{FSA} are fixed effects for year, month, and forward sortation area, respectively.

The empirical results reported in Col. 1 and 2 of OSA Table 1 indicate that the final sale price of a single-family house is significantly and positively correlated with property features such as the building and lot sizes, number of bedrooms and bathrooms, number of garages and driveways, and the dummy for the existence of the irregular lot size, and negatively affected by building age and the dummy for the existence of an air conditioner, an electronic baseboard, and the irregular building size.

Then we estimate the expected asking price of a house given the house's characteristics and the market conditions when the house becomes listed on the market. Due to a serious heteroskedasticity problem associated with the OLS model, we use the flexible general least square (FGLS) model proposed by Rutherford et al. (2005). We estimate the degree of overpricing, $DegreeOverpricing$, for each house by the error term of the asking price model (Anglin, Rutherford, and Springer, 2003; Rutherford et al., 2005).

The equations of the FGLS asking price model and the degree of overpricing, $DegreeOverpricing$, are:

$$ln(P_i^a) = \alpha_0 + \alpha_1\lambda_i + \sum \alpha_i X_i + F_{Year} + F_{Month} + F_{FSA} + \omega_i \quad (A19)$$

$$\omega_i = ln(P_i^a) - \widehat{ln(P_i^a)} \quad (A20)$$

where $ln(P_i^a)$ represents the natural log of the last asking price of house i. Standard errors are clustered at the FSA level.

The results reported in Col. 3 and 4 of OSA Table 1 exhibit similar relationships between the predicted last asking prices and house characteristics for the two estimation approaches; namely, an OLS model with standard errors clustered at the FSA level, and the FGLS model adjusted to account for heteroskedasticity. As was the case for the final sale price, the expected last asking price has the same directional correlations with similar covariates.

[OSA Table 1 about here.]

Online Supplementary Appendix 5 (OSA 5) – Robustness Checks

OSA 5.1 Robustness Check 1: Sample Selection Biases Tests

In this section, we check the possibility of sample selection biases in our main models because the final sale price is only observable for sold houses. We undertake the Heckman two-step selection model (Heckman, 1979). In the first step, we run a probit regression for the probability of house gets sold in the full sample of both expired and sold houses. Then, we calculate the inverse Mills ratio (IMR) by taking the ratio of the probability density function (PDF) to the cumulative distribution function (CDF) of the distribution. In the second step, we run an OLS regression of our baseline model, controlling for the IMR from the first step.

In OSA Table 2, results show that coefficients for all agent-type proxies in the Heckman two-stage selection models (Column 1, 3, and 5) are consistent with those coefficients in our baseline models (Column 2, 4, and 6), supporting the robustness of our baseline models.

[OSA Table 2 about here.]

OSA 5.2 Robustness Check 2: Omitted Variable Biases Tests

In this section, we check the possibility of omitted variable biases in our main models due to missing important variables. Therefore, we undertake a test based on Oster (2019). Based on the idea introduced by Oster (2019), we find out the identified set for each buying agent's type proxy and check the stability of their coefficients, respectively. The identified set is in the range between the estimated coefficient of our main models and the $\beta^{*\prime}$, which is derived using the following formula:

$$\beta^{*\prime} = \tilde{\beta} - \delta\left(\dot{\beta} - \tilde{\beta}\right) \frac{R_{max} - \tilde{R}}{\tilde{R} - \dot{R}} \qquad (A21)$$

In equation A21, $\tilde{\beta}$ and $\tilde{R}$ are the estimated coefficient and the R-square value of the main model. $\dot{\beta}$ and $\dot{R}$ are the estimated coefficient and the R-square value of the univariant regression model for each buying agent's type proxy without controlling for other variables and fixed effects. We calculate the value of R_{max} based on three approaches: Bellows and Miguel's (2009) value of $R_{max} = min(2.0\tilde{R}, 1)$, Mian and Sufi's (2014) value of $R_{max} = min(2.2\tilde{R}, 1)$, and the most conservative value of $R_{max} = 1$, respectively. When δ is equal to 1, this implies that the omitted variables and the included variables have the same level of influence on making the coefficient for the testing variable have a value of zero. If we find no zero included in the identified set, we conclude that the omitted variables do not drive our main results; otherwise, our main results are subject to omitted variable biases (Altonji et al., 2005).

In OSA Table 3, results show that all three identified sets that are based on the different values of R_{max} for each buying agent's type proxy do not include zero, supporting the robustness of our main models.

[OSA Table 3 about here.]

OSA 5.3 Robustness Check 3: Unobservable Brokerage Firm, Listing Agent, and Property Attributes

In this section, we conduct several robustness checks to assess the impacts of unobservable time-invariant attributes of the seller's brokerage firm and the buyer's brokerage firm by including brokerage firm fixed effects. For example, the reputation of the brokerage firms, which does not change frequently over the years, would possibly affect their agent's impact on the client. We also check the robustness of our main models by controlling for the impacts of unobservable time-invariant attributes of listing agents such as their education and gender, by including the listing agent fixed effect. Last, we consider the impact of unobservable time-invariant attributes of the property such as the front and back views of the house, on our main results by including property fixed effects in our baseline models.

In OSA Table 4, coefficients for each buying agent's type proxy show supportive results in most Columns. Except for coefficients for the average market share based on purchase amounts and commissions in Column 8 and Column 9, respectively, where the coefficients are positive but insignificant after controlling for the property fixed effects. All other coefficients of the buying agent's type proxies are significantly positive. In sum, we conclude that our main results are robust.

[OSA Table 4 about here.]

OSA 5.4 Robustness Check 4: Agent Heterogeneity in Bargaining Performance

Since we define high-type agents as those with better skills in predicting both buyers' and sellers' reservation prices and with stronger impacts on buyers, our main results may be driven by the buying agent's heterogeneity in their bargaining behaviors. For example, a high-type buying agent who has unfavorable outcomes for the buyer may have actually acted faithfully but just had worse bargaining performance, which resulted in her buyer buying the house at a high price. Therefore, we control for the effect of the buying agent's bargaining performance in our main models. Our control uses the current buying agent's past bargaining performance as a listing agent and as a buying agent, respectively. We calculate the exponential weighted average ratio of the final sale price to the last asking price of all transactions the buying agent was involved in as a listing agent (*AvPastSPtoLAPLA*) and as a buying agent (*AvPastSPtoLAPBA*), respectively, in the prior 5 years. One limitation of these proxies is that these measures reflect not only the buying agent's skills but also their self-interested level. Our theoretical model assumes that the interests of selling agents with sellers are aligned while those between buying agents with buyers are not aligned.

The most striking result in OSA Table 5 is that buying agents who had higher AvPastSPtoLAP when acting as listing or buying agents where their interests are expected to be aligned with seller had a higher current SalePrice/LastAP where their interests are not expected to be aligned with seller. All 6 coefficients are positive and significant at the 0.005 level (see Columns 1–6). When we control for the past bargaining performance of the current buying agent, we find that all 6 coefficients for our proxies for agent type are positive and all but two are significant at the 0.05 level. These insignificant coefficients are for the annual average market share based on the dollar amounts of purchases (Av%MktBuyAmt) in Column 2, and the annual average market share based on the commissions earned (Av%MktCommission) in Column 3. These results suggest that while the buying agent for the current house transaction acted faithfully when acting as the listing agent for a seller in past house transactions such does not carry over to that agent's behavior when acting as the buying agent for the buyer for the current house transaction. These results also suggest that the effect of further accounting for buying agent type for a current house transaction is lowered when one has already accounted for the past performance of the buying agent as a buying agent.

[OSA Table 5 about here.]

OSA 5.5 Robustness Check 5: Alternative Outcomes and Alternative Agent's Type Proxies

In this section, we check the robustness of our main results when the outcome variables are the natural log of the final sale price and the ratio of the final sale price to the original asking price, respectively. We test the stability of our results when each buying agent's type proxy is estimated by the exponential weighted average in the prior 3 years and in the prior year, respectively. We also use two alternative buying agent's type proxies, the buying agent's past average number of transactions in the prior 5 years (*Av#Transactions*) and the past average success rate of sales in the prior 5 years (*Av%SuccessSale*). Consistent with our main results, coefficients for each buying agent's type proxy are positive and significant in all panels in OSA Table 6.

[OSA Table 6 about here.]

OSA 5.6 Robustness Check 6: Financial Centers, Major Cities, and Regions with Most Listings

In this section, we check the robustness of our main results by running our main models using the Montreal sub-sample versus the non-Montreal sub-sample, the largest 6 cities sub-sample versus the non-largest 6 cities sub-sample based on the population in each city, and the top 5 regions and the non-top 5 regions based on the number of listings in each region. Consistent with our main results, coefficients for each sub-sample reported in OSA Table 7 are positive and significant.

[OSA Table 7 about here.]

OSA 5.7 Robustness Check 7: System of Simultaneous Equation Model

As argued by Turnbull and Dombrow (2006), Waller and Jubran (2012), and Turnbull and Waller (2018), amongst others, the listing time on the market and the selling price of houses are simultaneously determined. Therefore, in this section, we check the robustness of our main results by considering reverse causality between the listing time and the outcome variable in the main model, which is the ratio of the final sale price to the last asking price ($SPtoLastAP$). The simultaneous equations are:

$$\begin{aligned} SPtoLastAP_i = {} & \tau_0 + \rho\, ln(DOM_i) + \gamma(Agent' s\; Type\; Proxy)_i + \sum \omega_k (Main\; Controls)_i \\ & + House's\; Characteristics \; + \; Listing\; Agent' s\; Characteristics \\ & + \; F_{Year} + F_{Month} + F_{Region} + \epsilon_i \end{aligned} \qquad (A22)$$

$$\begin{aligned} ln(DOM_i) = {} & \tau_0{}' + \varpi SPtoLastAP_i + \gamma'(Agent' s\; Type\; Proxy)_i + \sum \omega'_n (Main\; Controls)_i \\ & + House's\; Characteristics \; + \; Listing\; Agent' s\; Characteristics \\ & + \; F_{Year} + F_{Month} + F_{Region} + \epsilon'_i \end{aligned} \qquad (A23)$$

$\ln(DOM_i)$ is the natural log of listing **days** on the market (DOM) for house i. $ListingDensity_i$ and $Competion_i$ are the listing density and competition variables that are used to make the system of simultaneous equations identified. For house i, we define competing house j as the one having the same number of bedrooms, the same property type, and being located in the same zip-code area (FSA). We also define the overlapping period on the market for competing houses as:

$$O(i,j) = min\big(creation\; date_i, creation\; date_j\big) - max(end\; date_i, end\; date_j) \qquad (A24)$$

The end date is the date when the house was sold or the date when the house was delisted. Because our data specify the creation time, the sale time, and the expiration time based on clock time there is no need to add an extra day to the overlapping period.

Since the distance information between two houses is not available, we roughly calculate the competition variable and the listing density variable using the following formulas:

$$Competion_i = \sum_j O(i,j) \qquad (A25)$$

$$ListingDensity_i = \frac{\sum_j O(i,j)}{DOM_i} \qquad (A26)$$

In OSA Table 8, the reported coefficients for the buying agent's type proxies on the ratio of the final sale price to the last asking price ($SPtoLastAP$) are consistent with the coefficients in Table 2. Also, consistent with previous studies (Turnbull and Dombrow, 2006; Waller and Jubran, 2012; and Turnbull and Waller, 2018; etc.), the listing time on market ($ln\,(DOM)$) has a significantly negative impact on $SPtoLastAP$. As expected, the positive and significant coefficient for listing density ($ListingDensity$) implies that houses sold in competitive environments yield higher $SPtoLastAP$. Based on the theory of the spatial competition effect and the shopping externality effect from Turnbull and Dombrow (2006), our results show that in terms of $SPtoLastAP$, the shopping externality effect more than offsets the spatial competition effect so that the net effect is an increase in the ratio of the final sale price to the last asking price.

In the time on market equation ($ln\,(DOM)$), the negative and significant coefficients for the ratio of the final sale price to the last asking price ($SPtoLastAP$) indicate that houses being sold at a low final sale price given the same last asking price are sold slower, consistent with the literature (Belkin, Hempel, and McLeavey, 1976; and Turnbull and Dombrow, 2006). This suggests that sellers are educated by the market over time and decrease their reservation prices over time and sell their houses at a lower price. The coefficient for the competition variable ($Competition$) is positive and significant, which indicates that in terms of the listing time, spatial competition more than offsets the shopping externality effect so that the net effect is an increase in the time on market.

[OSA Table 8 about here.]

OSA Table 1: Predicted Sale Price and Predicted Original Asking Price, 1994-2017

Dependent Variables:	Ln(SP)		Ln(LAP)	
Methodology	Heckman	OLS	Flexible-GLS	OLS
	(1)	(2)	(3)	(4)
Intercept	10.8528***	10.7970***	10.7118***	10.8899***
	(260.25)	(288.09)	(135.46)	(325.76)
FloorSize	0.0005***	0.0004***	0.0005***	0.0004***
	(199.92)	(43.61)	(37.30)	(47.34)
FloorSizeSq	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(-126.35)	(-24.58)	(-18.49)	(-26.83)
LotSize	0.0000***	0.0000***	-0.0000	0.0000***
	(86.82)	(11.36)	(-0.48)	(17.14)
LotSizeSq	-0.0000***	-0.0000***	0.0000	-0.0000***
	(-57.47)	(-8.84)	(1.65)	(-14.09)
#TotalBedrooms	0.0246***	0.0256***	0.0362***	0.0211***
	(61.23)	(14.01)	(13.80)	(11.39)
#TotalBathrooms	0.0943***	0.0883***	0.1081***	0.1008***
	(140.56)	(24.16)	(23.09)	(21.24)
Age	-0.0057***	-0.0056***	-0.0050***	-0.0048***
	(-320.52)	(-38.97)	(-16.24)	(-33.52)
#Driveway	0.0076***	0.0070***	-0.0018	0.0073***
	(38.91)	(9.15)	(-1.83)	(10.59)
#Garage	0.0587***	0.0515***	0.0596***	0.0573***
	(101.99)	(29.75)	(23.09)	(34.98)
DumForcedAir	-0.0071***	-0.0086***	0.0339***	-0.0065*
	(-6.91)	(-2.83)	(5.38)	(-2.04)
DumEleBase	-0.0275***	-0.0314***	-0.0421***	-0.0364***
	(-30.08)	(-13.82)	(-14.17)	(-16.87)
DumIrrBuilding	-0.0048***	-0.0012	0.0043	-0.0022
	(-5.72)	(-0.77)	(1.64)	(-1.48)
DumIrrLot	0.0129***	0.0103***	0.0080***	0.0156***
	(16.65)	(5.93)	(3.17)	(8.09)
Year/Month FE	Yes	Yes	Yes	Yes
Region or FSA FE	FSA	FSA	Region	FSA
Building Type FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
Observations	942,458	579,060	942,458	942,458
R-squared	N/A	0.8378	0.7682	0.8151
Lambda	-0.1991***	N/A	N/A	N/A
SE clustered	No	FSA Level	FSA Level	FSA Level

Notes: Column 1 and Column 2 report results from Heckman Selection model and OLS model on predicting the sale price of the house, respectively. Column 3 and Column 4 report results from flexible general least square model (FGLS) and OLS model on predicting the last asking price of the house. We include the year, month, and FSA (Forward Sortation Area) fixed effects in Columns 1, 2, and 4 and the year, month, and region fixed effects in Column 3. We report the critical statistics in the parentheses. We cluster the standard errors at the FSA level in all models except for the Heckman Selection model. The full estimation samples for all models include single-family houses in Quebec province listed on the MLS during the 1994-2017 period. Statistics with significance at 0.5% level are denoted with ***, at 1% level with **, and at 5% with *.

OSA Table 2: Robustness Check: Sample Selection Biases Test, Heckman Selection Model, 2005-2017

Dependent Variable:	SalePrice/LastAP (SPtoLastAP)					
	(1)	(2)	(3)	(4)	(5)	(6)
Av#Purchases	0.00012***	0.00012***				
	(10.38)	(5.15)				
AvMkt%BuyAmt			0.07931***	0.07928**		
			(7.75)	(2.64)		
AvMkt%Commission					0.05639***	0.05688*
					(5.49)	(2.16)
HseCharacteristics	Yes	No	Yes	No	Yes	No
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes
Listing Agent Chara.	Yes	Yes	Yes	Yes	Yes	Yes
Year/Month/Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	656,712	359,122	602,724	305,141	568,435	270,856
R-squared		0.18758		0.18872		0.18498
Lambda	-0.00515***		-0.00522***		-0.00600***	

Notes: This table reports results from Heckman selection models and our baseline models that test the impact of buying agent heterogeneity on the ratio of the final sale price to the last asking price (*SPtoLastAP*). Columns 1, 3, and 5 include the inverse Mill ratio (IMR) from the probit model in the first step of the two-step Heckman selection model. Columns 2, 4, and 6 are results from baseline models. All columns control for house characteristics, listing agent characteristics, and year, month, and region fixed effects. Main controls are the same as control variables in Table 2. We report the t-values in the parentheses. Standard errors in Column 2, 4, 6 are clustered at the FSA and the year-month levels. The estimation samples for all models include single-family houses listed on the MLS during the 2005-2017 period. Statistics with significance at 0.5% level are denoted with ***, at 1% level with **, and at 5% level with *.

OSA Table 3: Robustness Check: Omitted Variable Biases Tests

Dependent Variable:	SalePrice/LastAP (SPtoLastAP)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Uncontrolled	Controlled	Bellows and Miguel (2009) $R_{max} = 2\tilde{R} - R$	Mian and Sufi (2014) $R_{max} = 2.2\tilde{R} - R$	Most conservative case $R_{max} = 1$	Include Zeros?
Panel A: Average number of purchases						
Av#Purchases	-0.00029*** (-6.40)	0.00012*** (5.15)	[0.00012, 0.00053]	[0.00012, 0.00061]	[0.00012. 0.00193]	**No**
R^2	0.0042	0.1876				
R_{max}			0.3709	0.4085	1.0000	
Observations	359,122					
Panel B: Average market share based on purchases amounts						
AvMkt%BuyAmt	-0.24908* (-2.55)	0.07928** (2.64)	[0.07928, 0.40763]	[0.07928, 0.47558]	[0.07928, 1.53984]	**No**
R^2	0.0063	0.1887				
R_{max}			0.3711	0.4089	1.0000	
Observations	305,141					
Panel C: Average market share based on commission						
AvMkt%Commission	-0.24423** (-2.70)	0.05688* (2.16)	[0.05688, 0.35800]	[0.05688, 0.42002]	[0.05688, 1.42319]	**No**
R^2	0.0054	0.1850				
R_{max}			0.36460	0.40159	1.0000	
Observations	270,856					
Main Control Variables	No	Yes				
House Chara.	No	Yes				
Listing Agent Chara.	No	Yes				
Top Brokerage Dummy	No	Yes				
Year/Month/Region FE	No	Yes				

Note: This table reports the Oster (2019) bounds for our variables of interest in our main (baseline) model. Our dependent variable is *SPtoLastAP* and our main research variables are *Av#Purchases* (Panel A), *AvMkt%BuyAmt* (Panel B), and *AvMkt%Commission* (Panel C). Column 1 and Column 2 in each panel illustrate the results from the uncontrolled and controlled model, respectively. Column 3 in each panel represents the Oster bounds with the Bellows and Miguel (2009) assumption of δ=1 and R_{max} =min($2\tilde{R} - R$, 1). Column 4 in each panel represents the Oster bounds with the Mian and Sufi (2014) assumption of δ=1 and R_{max}=min($2.2\tilde{R} - R$, 1). Column 5 in each panel represents the Oster bounds with the most extreme assumption of δ=1 and R_{max}=1.

OSA Table 4: Robustness check: Unobservable Brokerage Firm, Listing Agent, and Property Attributes, 2005 - 2017

Dependent Variable:	SalePrice/LastAP (SPtoLastAP)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Av#Purchases	0.00007***			0.00005***			0.00007*		
	(3.96)			(3.01)			(2.04)		
AvMkt%BuyAmt		0.05850*			0.06463***			0.02192	
		(2.19)			(2.95)			(0.44)	
AvMkt%Commission			0.02892			0.04543**			0.07375
			(1.40)			(2.75)			(0.96)
Main Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
House Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Listing Agent Characteristics	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Year/Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Brokerage Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Listing Agent FE	No	No	No	Yes	Yes	Yes	No	No	No
Property FE	No	No	No	No	No	No	Yes	Yes	Yes
Observations	358,630	304,604	270,305	355,878	301,632	267,263	87,384	64,858	53,122
R-squared	0.21397	0.21547	0.21322	0.27034	0.27378	0.27682	0.59295	0.59846	0.59712

Notes: This table reports robustness checks for the baseline model that tests the impact of the buying agent heterogeneity on the ratio of the final sale price to the last asking price (*SPtoLastAP*). Columns 1, 2, and 3 check the unobservable time-invariant brokerage firm attributes by controlling for buying agent and listing agent brokerage firms fixed effects. Columns 4, 5, and 6 check the unobservable time-invariant listing agent attributes by controlling for brokerage firms fixed effects and the listing agent fixed effect. Columns 7, 8, and 9 check the unobservable time-invariant property attributes by controlling for property fixed effect. Unreported main controls include *Ln(MOM)*, *#ListingAgents, #BuyingAgents*, *#ActiveYrs*, *LABusyness*, *BABusyness*, *DOP*, *ContractDuration*, *DumPriceInc*, *DumPriceDec*, *DumUrban*, *DumDualAgent* in all columns. We further include top brokerage firm dummy variables, *DumTopBuyingBrokerage*, and *DumTopListingBrokerage*, in Columns 7, 8, and 9. The estimation samples cover single-family houses in Quebec listed on the MLS during the 2005-2017 period. We report t-values in the parentheses based on standard errors clustered at the FSA and year-month levels. Statistics with significance at 0.5% level are denoted with ***, at 1% level with **, at 5% level with *.

OSA Table 5: Robustness Check: Agent Heterogeneity and Sale Price to Last Asking Price Ratio with Controls for Past Bargaining Performance, 2005-2017

Dependent Variable:	SalePrice/LastAP (SPtoLastAP)					
	(1)	(2)	(3)	(4)	(5)	(6)
Av#Purchases	0.00004*			0.00006*		
	(2.17)			(2.58)		
AvMkt%BuyAmt		0.02018			0.05124*	
		(0.87)			(2.14)	
AvMkt%Commission			0.01736			0.04944*
			(0.78)			(2.21)
AvPastSPtoLAPBA	0.29600***	0.30167***	0.29774***			
	(20.61)	(19.22)	(17.58)			
AvPastSPtoLAPLA				0.27774***	0.28432***	0.28167***
				(18.23)	(17.46)	(15.89)
HseCharacteristics	Yes	No	Yes	No	Yes	No
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes
Listing Agent Chara.	Yes	Yes	Yes	Yes	Yes	Yes
Year/Month/Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	305,720	274,763	238,459	263,267	234,425	202,469
R-squared	0.20363	0.20450	0.20083	0.20165	0.20255	0.19916

Notes: This table reports results from OLS regressions that test the impact of buying agent heterogeneity on the ratio of the final sale price to the last asking price (*SPtoLastAP*), controlling for the buying agent's past bargaining performance as buying agent (*AvPastSPtoLAPBA*) and as listing agent (*AvPastSPtoLAPLA*), respectively. Columns 1 and 4 include the annual average number of purchases a buying agent was involved in the prior 5 years (*Av#Purchases*) to identify buying agent heterogeneity. Columns 2 and 5 include the annual average market share of the buying agent based on the dollar amount of purchases in the prior 5 years (*AvMkt%BuyAmt*) to identify buying agent heterogeneity. Columns 3 and 6 include the annual average market shares of the buying agent based on the commission earned in the prior 5 years (*AvMkt%Commission*) to identify buying agent heterogeneity. All columns control for house characteristics, listing agent characteristics, and year, month, and region fixed effects. Main controls are the same as control variables in Table 2. We report the t-values in the parentheses based on standard errors clustered at the FSA and the year-month levels. The estimation samples for all models include single-family houses listed on the MLS during the 2005-2017 period. Statistics with significance at 0.5% level are denoted with ***, at 1% level with **, and at 5% level with *.

OSA Table 6: Robustness Check: Performance Aternates and Agent's Type Alternates, 2005-2017

Panel A: Final Sale Price			
Dependent Var.:	Natural Log of Final Sale Price (lnSP)		
	(1)	(2)	(3)
Av#Purchases	0.00014***		
	(5.22)		
AvMkt%BuyAmt		0.09003**	
		(2.69)	
AvMkt%Commission			0.06542*
			(2.26)
Main Control Var.	Yes	Yes	Yes
House Chara.	Yes	Yes	Yes
Listing Agent Chara.	Yes	Yes	Yes
Year/Month/Region FE	Yes	Yes	Yes
Observations	359,122	305,141	270,856
R-squared	0.99309	0.99290	0.99287

Panel B: Sale Price to Original Asking Price						
Dependent Var.:	SalePrice/OriginalAP (SPtoOriginalAP)					
	(1)	(2)	(3)	(4)	(5)	(6)
Av#Purchases	0.00015***	0.00017***				
	(5.56)	(6.28)				
AvMkt%BuyAmt			0.08173***	0.10333***		
			(3.26)	(3.47)		
AvMkt%Commission					0.05060*	0.06306**
					(2.43)	(2.83)
Main Control Var.	Yes	Yes	Yes	Yes	Yes	Yes
House Chara.	Yes	No	Yes	No	Yes	No
Listing Agent Chara.	Yes	Yes	Yes	Yes	Yes	Yes
Year/Month/Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	359,122	359,122	305,141	305,141	270,856	270,856
R-squared	0.42870	0.38718	0.42828	0.38669	0.42895	0.38684

Panel C: Buying Agent Type with Three-year Average						
Dependent Var.:	SalePrice/LastAP (SPtoLastAP)					
	(1)	(2)	(3)	(4)	(5)	(6)
Av#Purchases3Yrs	0.00012***	0.00014***				
	(5.38)	(6.30)				
AvMkt%BuyAmt3Yrs			0.08991**	0.10330***		
			(2.76)	(2.86)		
AvMkt%Commission3Yrs					0.06367**	0.07241**
					(2.70)	(2.80)
Main Control Var.	Yes	Yes	Yes	Yes	Yes	Yes
House Chara.	Yes	No	Yes	No	Yes	No
Listing Agent Chara.	Yes	Yes	Yes	Yes	Yes	Yes
Year/Month/Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	359,122	359,122	331,160	331,160	315,417	315,417
R-squared	0.18760	0.14262	0.18866	0.14337	0.18614	0.14042

Panel D: Buying Agent Type with Prior One-year Activities						
Dependent Var.:	SalePrice/LastAP (SPtoLastAP)					
	(1)	(2)	(3)	(4)	(5)	(6)
Av#Purchases1Yr	0.00010***	0.00012***				
	(5.86)	(6.82)				
AvMkt%BuyAmt1Yr			0.07987***	0.09068***		
			(3.06)	(3.15)		
AvMkt%Commission1Yr					0.06502***	0.07201***
					(2.93)	(3.05)
Main Control Var.	Yes	Yes	Yes	Yes	Yes	Yes
House Chara.	Yes	No	Yes	No	Yes	No
Listing Agent Chara.	Yes	Yes	Yes	Yes	Yes	Yes
Year/Month/Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	359,122	359,122	359,122	359,122	359,042	359,042
R-squared	0.18758	0.14260	0.18753	0.14251	0.18744	0.14241

Panel E: Additional Agent Heterogeneity Alternates				
Dependent Variable:	SalePrice/LastAP (SPtoLastAP)			
	(1)	(2)	(3)	(4)
Av#Transactions	0.00004***	0.00005***		
	(3.28)	(3.77)		
Av%SuccessSale			0.00487***	0.00584***
			(7.81)	(8.14)
Main Controls Var.	Yes	Yes	Yes	Yes
House Chara.	Yes	No	Yes	No
Listing Agent Chara.	Yes	Yes	Yes	Yes
Year/Month/Region FE	Yes	Yes	Yes	Yes
Observations	356,871	356,871	345,743	345,743
R-squared	0.18733	0.14229	0.18804	0.14286

Notes: The panels in this table report results of robustness checks for the bargaining outcome and buying agent heterogeneity measures in the baseline model. Panel A and B report results from OLS regressions that test the impact of buying agent heterogeneity on the natural log of the final sale price (*lnSP*) and on the ratio of the final sale price to the original asking price (*SPtoOriginalAP*), respectively. Panels C and D report results from OLS regression that test the impact of buying agent heterogeneity, which is measured by the annual average number of purchases a buying agent was involved in, the annual average market share of the buying agent based on the dollar amount of purchase, and the annual average market share of the buying agent based on commissions earned in the prior **THREE** years (*Av#Purchases3Yrs*, *AvMkt%BuyAmt3Yrs*, and *AvMkt%Commission3Yrs*) and in the prior **ONE** year (*Av#Purchases1Yr*, *AvMkt%BuyAmt1Yr*, and *AvMkt%Commission1Yr*). Panel E reports results from OLS regressions that test the impact of buying agent heterogeneity, which is measured by the annual average number of transactions (both listings and purchases) a buying agent was involved in during the prior 5 years (*Av#Transactions*) and the proportion of successful sales a buying agent participated in during the prior 5 years (*Av%SuccessSales*). Unreported main controls include *Ln(MOM)*, *#ListingAgents*, *#BuyingAgents*, *#ActiveYrs*, *LABusyness*, *BABusyness*, *DOP*, *ContractDuration*, *DumPriceInc*, *DumPriceDec*, *DumUrban*, *DumDualAgent*, *DumTopBuyingBrokerage*, and *DumTopListingBrokerage*. All models control for house characteristics, listing agent characteristics and year, month, and region fixed effects. We report the t-values in the parentheses based on standard errors clustered at the FSA and the year-month levels. The estimation samples for all models include single-family houses listed on the MLS during the 2005-2017 period. Statistics with significance at 0.5% level are denoted with ***, at 1% level with **, and at 5% level with *.

OSA Table 7: Robustness Check: Financial Centers, Largest Six Cities, and Top Five Regions with Most Listings, 2005-2017

Dependent Variable:	SalePrice/LastAP (SPtoLastAP)					
Panel A: Financial Centers	**Montreal**			**Non-Montreal**		
	(1)	(2)	(3)	(4)	(5)	(6)
Av#Purchases	0.00020**			0.00012***		
	(2.63)			(4.81)		
AvMkt%BuyAmt		0.22098			0.07462*	
		(0.60)			(2.49)	
AvMkt%Commission			0.22992			0.05372*
			(0.77)			(2.01)
Observations	35,405	24,836	23,619	323,716	280,304	247,236
R-squared	0.19730	0.20188	0.20445	0.19343	0.19359	0.19001
Panel B: Largest Six Cities (Population)	**Largest Six Cities**			**Non-Largest Six Cities**		
	(1)	(2)	(3)	(4)	(5)	(6)
Av#Purchases	0.00007*			0.00013***		
	(2.13)			(4.82)		
AvMkt%BuyAmt		0.03280			0.07888*	
		(0.46)			(2.56)	
AvMkt%Commission			-0.06565			0.05943*
			(-0.87)			(2.15)
Observations	66,734	55,848	45,147	292,388	249,293	225,709
R-squared	0.17154	0.17503	0.17213	0.19105	0.19077	0.18746
Panel C: Top Five Regions (# of Listings)	Top Five Regions			Non-Top Five Regions		
	(1)	(2)	(3)	(4)	(5)	(6)
Av#Purchases	0.00013***			0.00010*		
	(5.34)			(2.38)		
AvMkt%BuyAmt		0.18849			0.05422	
		(0.85)			(1.75)	
AvMkt%Commission			-0.17854			0.04205
			(-0.81)			(1.39)
Observations	253,523	211,973	197,669	105,599	93,168	73,187
R-squared	0.16445	0.16595	0.16523	0.21930	0.21763	0.21869
Main Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
House Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Listing Agent Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year/Month/Region FE (Municipal FE for Montreal Subsample)	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The panels of this table report results from OLS regressions for each subsample that test the impact of buying agent heterogeneity on the ratio of the final sale price to the last asking price (*SPtoOLastAP*). Panel A reports results for the Montreal sub-sample and the Non-Montreal subsample, respectively. Panel B reports results for the Largest Six Cities sub-sample based on their population and the Non-Largest Six Cities sub-sample, respectively. Panel C reports results for the Top Five Regions sub-sample based on their number of listings and the Non-Top Five Regions sub-sample, respectively. Unreported main controls include *Ln(MOM)*, *#ListingAgents*, *#BuyingAgents*, *#ActiveYrs*, *LABusyness*, *BABusyness*, *DOP*, *ContractDuration*, *DumPriceInc*, *DumPriceDec*, *DumUrban*, *DumDualAgent*, *DumTopBuyingBrokerage*, and *DumTopListingBrokerage*. We report the t-values in the parentheses based on standard errors clustered at the FSA and the year-month levels. The full estimation samples for all models include single-family houses in Quebec province listed on the MLS during the 2005-2017 period. Statistics with significance at 0.5% level are denoted with ***, at 1% level with **, and at 5% level with *.

OSA Table 8: Robustness Check: System of Simultaneous Equation Model, 2005-2017

Dependent Variable:	SPtoLastAP	Ln(DOM)	SPtoLastAP	Ln(DOM)	SPtoLastAP	Ln(DOM)
	(1)	(2)	(3)	(4)	(5)	(6)
Av#Purchases	0.00007***					
	(7.27)					
AvMkt%BuyAmt			0.05153***			
			(6.29)			
AvMkt%Commission					0.03820***	
					(4.55)	
SPtoLastAP		-14.39362***		-15.28475***		-14.52282***
		(-49.02)		(-47.95)		(-42.82)
Ln(DOM)	-0.02145***		-0.02221***		-0.02166***	
	(-55.41)		(-53.09)		(-47.99)	
ListingDensity	0.00002***		0.00002***		0.00002***	
	(16.29)		(15.84)		(13.51)	
Competition		0.00001***		0.00001***		0.00001***
		(54.07)		(48.60)		(47.11)
Main Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
House Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Listing Agent Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year/Month/Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	359,179	359,179	305,191	305,191	270,902	270,902
R-squared	0.09572	0.39166	0.08882	0.37075	0.09050	0.38950

Notes: This table reports the results using 3SLS simultaneous equations for the ratio of the final sale price to the last asking price of a house and its listing time on the market (in days). Columns 1, 3, and 5 report the results for the price equation, in which the dependent variable is *SPtoLastAP*, and Columns 2, 4, and 6 report the results for the time equation, in which the dependent variable is *Ln(DOM). ListingDensity* and *Competition* variables measure the concentration of listings in neighborhoods and ensure the identification of each equation. Unreported main control variables for the price equations include *Ln(MOM)*, *#ListingAgents*, *#BuyingAgents*, *#ActiveYrs*, *LABusyness*, *BABusyness*, *DOP*, *ContractDuration*, *DumPriceInc*, *DumPriceDec*, *DumUrban*, *DumDualAgent*, *DumTopBuyingBrokerage*, and *DumTopListingBrokerage*. Unreported main control variables for the time equations include *Ln(MOM)*, *#ListingAgents*, *LABusyness*, *DOP*, *ContractDuration*, *DumPriceInc*, *DumPriceDec*, and *DumUrban*. We control for house characteristics, listing agent characteristics, and the year, month, region fixed effects in each model and report the critical statistics in the parentheses. The full estimation samples cover single-family houses in Quebec province listed on the MLS during the 2005-2017 period. Statistics with 0.5% level of significance are denoted with ***, at 1% level with **, and at 5% level with ***.