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The impact of competition on experts' information disclosure : the case of real estate brokers

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Abstract

Competition can theoretically counter or reinforce tendency of experts to pass biased information to customers. Using data from an online company connecting real estate brokers with clients who want to sell their properties, we show that more competition or lower opportunity to collude induce brokers to raise their initial price estimation by more than 3%. This is observed upstream, when experts appraise the property for sale. Competition partially prevents brokers from biasing downward evaluations, and is beneficial to the client since it translates into a positive effect on listing and sale prices with no significant effect on the time to sale.

Keywords: Information revelation; Competition; Price appraisal; Real Estate Brokers;

JEL Codes: L15 - D8 - D83 - R30 - L85

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1 Introduction

Individuals and firms often rely on experts to guide their decision-making. Somehow, interest of clients and advisors are often not aligned, which may result in biased advices. Such phenomena has been empirically observed in many sectors of activity, especially in service markets in which sellers are also those who diagnose the needs, such as automobile repair or home heating. They have therefore an incentive to shade their reports on consumers' condition in order to increase their short-term sales, or on the contrary have an interest in being lenient in the case of mandatory inspection so as to retain their customer (Hubbard, 1998; Schneider, 2012). For similar reasons, real estate agents underestimate the houses they are selling (Rutherford et al., 2005; Levitt and Syverson, 2008), while financial advisors may put more risk on their clients to increase their commissions (Hackethal et al., 2012). [1]

The behavior of experts, namely their tendency to distort or report the truth, depends closely on the options available to their client. In the seminal work of Crawford and Sobel (1982), the expert merely sends a non-binding and non-costly information ("cheap talk") and the principal decides freely among all possible choices. Other strands of literature have since developed to take into account that this choice may be more constrained, e.g. limited to finite set partially defined by agents like in closed legislative rule (Gilligan and Krehbiel, 1989) or by a partial pre-commitment defined within a firm (Alonso and Matouschek, 2008), or on the contrary broader with some outside option detrimental to the expert (Che et al., 2013). As regards the latter case, the expert faces a second conflict of interest, namely to avoid that his client chooses the outside option, which may led him to distort his recommendation in the direction of their client's prior beliefs. Such strategic behavior can be also induced by the fear of losing a customer to the benefit of a competitor. Competitive pressure can thus hinder efficient information transmission because experts prefer to cater excessively to their customers' opinon, as analyzed by Hei-

[1] This phenomenon corresponds also to the supplier-induced demand hypothesis in health economics (Evans, 1974), according to which physicians recommend more health care purchases than patients would buy if they had the same information.

dhues and Lagerlöf (2003) in the case of electoral competition and Cummins and Nyman (2005) in a delegated investment framework. It may reversely also improve information transmission when experts are not biased in the same direction as in shown by Krishna and Morgan (2001), or simply when catering counteract the tendency to strategically lie.

The objective of this work is to assess empirically the effect of competition on information disclosure by experts in a specific context of real estate agents intermediated by an internet platform. Empirical work on that matter is scarce and concerns other industries where reputation and repeated interactions plays a key role. [2] Bolton et al. (2012) survey empirical papers on credit agencies and build a model that shows, consistent with observation, that competition among those agencies results in excessively high reported ratings, despite reputation costs, because issuers shop for good rating. Flynn and Ghent (2017) confirm this influence of competition on ratings by empirically analyzing the impact of a new entrant. A similar mechanism plays in the real estate appraisal industry as empirically assessed in a recent work. [3] Hubbard (1998) and Hubbard (2002) highlight the role of reputational incentives in the vehicle emission inspection market, by showing that inspection failure rates is less than half when conducted by private firms rather than by state officials, and that consumers are 30% more likely to choose a firm at which their vehicle previously passed. By contrast, in the case considered here with real estate agents, reputational effects are largely absent. [4] Such experts have mainly aligned interests in that they all seek to sell quickly even if at a lower price than desired by sellers as men-

[2] Agarwal et al. (2015) indirectly confirm the role of competition between experts in the valuation of real estate. They show that borrowers are able to influence experts conducting appraisals in order to increase their borrowing or lower their interest rate.

[3] Appraisers cater to loan officer by overstating collateral value, as loan officers first go to appraisers whose reputation is to deliver appraisals at least as high as the transaction price. Conklin et al. (2019) show that competition reinforces this bias.

[4] Indeed, the sale of a house is a relatively rare event, so that individuals can not accumulate information through regular interactions with real estate agents. Historical data on brokers are starting to be available on internet, but this was not yet the case in the context and during the period considered here. Another reputational mechanism operates through the recommendations provided to a seller by close friends and acquaintances, as studied by Shi and Tapia (2016), but in our empirical analysis, brokers are selected by a third party.

tioned before. As explained at the beginning of section 3 of this paper, and illustrated by a simple theoretical model developed in an appendix, competition has an ambiguous effect in such framework because multiple effects are in play. [5] In particular, competitive pressure may prevent the broker from biasing downward his estimate (for fear of losing the client) or induce him to bias it upwards (in order to capture a client). The empirical question addressed here is whether the sheer pressure of competitors is enough to correct this tendency to skew downward housing estimates, even in the absence of reputational effects and repeated interactions, or whether it make things worse for customers.

In order to do so, we use data on the Parisian housing market between 2013 and 2019 provided by "MeilleursAgents.com" (hereafter "MA") an online real estate companies which helps potential sellers to find real estate agents in their neighborhood. Each client of their website (a potential seller) is put in relationships with agents who estimate the value of the property that the client wishes to sell, and may then act as a broker to this client. More precisely, regarding one of the main offer of MA called Liberty that will serve as benchmark in the following, each seller is put in relationships with two agents. After receiving their separate estimates, he may then decide to sign a mandate with zero, one or both real estate agents. In the case where the client signs a mandate with at least one agent, we observe a listing price, whether the property is sold and the selling price.

Two distinct phases can be distinguished in this bargaining process. The first phase is the "appraisal phase". The client can first indicate his preferences and beliefs by telling what is his ideal and/or minimum selling price on the website. Agents then visit the house and send separate estimates of the property. During this phase, messages are non-costly and do not imply an explicit commitment: agents and client can highlight other factors (such as market liquidity and time constraints) in order to change their position, and then negotiate the listing price on another basis. However, this phase can not be qualified as a pure "cheap talk" because the final decision about the listing price is not

[5] This ambiguous impact is a general feature of competition. In particular, Gentzkow and Kamenica (2016) consider experts with a common prior who decide to conduct publicly observed experiment about an unknown state of the world and show that the impact of competition on information revelation is ambiguous.

completely in the hands of the client, but will result from a negotiation (unless he decides to quit the negotiation and sells on his own). This is what happens in the more engaging "sales phase" which begins with the agreement on a listing price and eventually leads to a sale.

In this paper, we use as sources of variation multiple variants of this process, which either increase competition or induce collusion during the appraisal phase. Our main source of variations use the fact that MA decided in 2016 to increase the number of agents to three on a local basis, once the online company was able to contract locally with a third broker. This strengthening of competitive pressure may be partly endogenous, as it depends on MA's ability to find and contract with new brokers, and on their availability when new prospects arrive. However, by including multiple fixed effects (geographical zones, real estate agents and months), we are able to control this potential bias and measure how a broker's strategy evolves when faced with two instead of a single competitor for a given prospect. Two other sources of variation are also used, which proxy respectively explicit and potential collusion. First, MA offers an alternative process named 'Serenity' in which MA collects price estimates from both agents and negotiates a listing strategy directly with the seller. Then both agents get a similar mandate or none. Thus, in this offer, the two real estate agents do not compete for new listings, but only once they get a mandate to sell the property. Secondly, we consider interactions between agents, as a source of potential collusion. More precisely, we use as sources of variation both past contacts (number of interactions through MA between two brokers) and during-the-sale's contacts (when the two agents visit the dwelling within the same time window of less than half an hour,).

We first focus on the appraisal phase during which those alternatives are respectively equivalent to compare two competing agents versus three competing agents, and versus implicit or explicit collusion between agents (explicit when there is delegation to single representative). The core empirical results are obtained on real estate brokers' estimation of housing value. Subsequent analyzes are then conducted on the remaining data downstream of the sales process: selected listing price when a mandate is granted by the client, time on the market and sale price. We acknowledge potential endogeneity problems regarding the sources of variation used as a proxy of collusion : clients decide on the process (Liberty or Serenity) and influence the choice of times of visit. Somehow, even if important characteristics of clients (such as "bargaining skills" or "loss aversion") are impossible to observe, we are able to control for hedonic housing characteristics as well as for particularities stated by clients (such as "reasons to sell"). We run also additional tests, in particular by controlling with the purchase price of the apartment for sale, and by removing sales prospect that are interrupted by the seller (when no contract is signed with one of the brokers). Finally, the fact that those multiple sources of variations lead to the same conclusion, and that the first one is well controlled for endogeneity, confirms the robustness of the overall result presented in this work.

All other things being equal, we find that removing collusion and increasing competition have significant and positive on the valuation of properties by agents. More precisely, a reinforcement of the competition with the addition of a third competing agent results in about 3% increase in the valuation. Besides, housing units are estimated in the Liberty process with two agents at values more than 5% higher than in the Serenity process, whereas the estimated prices decrease by about 3% when real estate agents both visit the property within the same time window. [6] These results must be seen in the light of the above-mentioned works of Rutherford et al. (2005) and Levitt and Syverson (2008). These two studies both show that agent-owned houses sell at a price higher than client-owned houses, with a price premium equal respectively to 3.7% and 4.5%, because agents exploit their informational advantage to convince their clients to sell their house too cheaply. Our results show that strengthening the competition between brokers for new clients can significantly help to stop this downward bias.[7] Besides, they rule out in a robust way the other potential explanations, e.g. a lower priced client-owned houses may

[6] We observe also a price decrease of 2% when the number of past interactions between the two brokers is in the top decile instead of the median.

[7] Shi and Tapia (2016) observe that housings are sold at a similar discount (around 3%) when sellers leave the region, and show that this can be partly attributed to the lack of reputational effect - once in another region, such sellers are less able to recommend the broker to their acquaintances.

result from less effort from the broker during the selling process, or may simply reflect the fact that agent-owned houses are of better quality. We show that a manipulation of information takes place at the very beginning of the interaction between the broker and his client, when the former provides his first estimate of the property for sale.

To our knowledge, this is the first time that an empirical analysis is conducted as far upstream of such a negotiation process between an expert and his client. The data collected allow us to go further in this analysis, by using the preferential sales prices given by some clients at the beginning of the exchange with MA. We notice spikes in the distribution of estimated prices at the prices indicated by clients, and the excess mass in the distribution rejects a simple story of convenience rounding. In other words, pandering to client's wishes by aligning his evaluation on the desired price is part of the broker's strategy. We show that this explains partly what has been observed previously. In particular, the increase in competition when using Liberty instead of Serenity induces agents to resort more often to this strategy. But this is only a small part of the explanation, which means that broker's strategies to attract clients are more sophisticated than that: the previously mentioned empirical results on the impact of competition remain unchanged when we control this behavior.

The analysis of the subsequent sales phase shows that these competition effects persist on the entire sales process. More precisely, the impact on the listing price is significant - about 4% for each of the three sources of variation. Similar effects are founded on the sale price when a sale occurs. In particular, when moving from the colluding Serenity to Liberty with two competing agents (resp. when the two agents do not visit at the same time), the sale price increases by about 5% (resp. 7%). In order to determine whether the competition ultimately benefits customers, it remains to analyze the effect on selling time, as measured by the TOM (time on the market). Indeed, a higher selling price is not necessarily beneficial for the customer, especially if it leads to an excessive lengthening of the sales process. On the contrary, some homeowners may accept a low listing price in a hurry to sell faster. However, we see no impact on the TOM when we use the third source of variation in competition (potential collusion during the time of visit) whereas the shift from 2 to 3 agents leads to a lower TOM even when we control by the number of given mandates. [8] All this shows that the observed impact of competition result from an overall improvement in the quality of information exchanged between agents and their clients. The resulting higher price has no negative effect on the time of sale as the agent adjusts his efforts during the selling process accordingly. Competition prevents brokers from skewing their estimates downward and from relaxing their effort afterwards, thus benefits to sellers by driving sales at higher prices without slowing down the process.

This work also allows us to better understand the evolution of the strategy of an internet platform on its two-sided market. Initially, MA's choices regarding its negotiation process are partly in favor of the brokers. They have an interest in joining the internet platform in order to obtain sales prospect with limited competition. Over the past few years, MA has gradually increased competition (3 instead of 2 brokers) and limited collusion (prioritizing the liberty's process instead of serenity) for the benefit of sellers. It is worth noting that they have decided in 2020 to provide detailed informations on brokers on their website (including performance history). This is consistent with theory (Rochet and Tirole, 2003), such platforms usually first focus on one side of the market, which is determinant to get the other side "on board". [9]

The paper is organized as follows. Section II introduces the data used. Section III presents the main empirical analysis, which focuses on the impact of competition and coordination on real estate agents' estimated values. Section IV provides two complementary analysis, respectively on the sale process (listing price, selling price, and time on the market) and on the strategies of complying with clients' wishes. The final section of the paper, section V, summarizes the result and offers some concluding remarks.

[8] In other words, the mere fact that the client has been in contact with two other agents seems to be enough to put pressure on the broker who hurries to sell.

[9] In the case of MA, sellers looking for precise data on the real estate market came naturally to their site, and the main difficulty remained to contract with real estate agents in order to respond to sellers' need. The stake today for this company is more balanced and oriented towards increasing their market share (measured as the share of sales that goes through them).

2 Data and sample

2.1 Data source and sales process

We obtain our data from "MeilleursAgents.com" (MA), a firm which provides online estimations of real estate prices and connects potential sellers with real estate agents with whom they have previously negotiated commission levels. The typical process can be divided in five steps defined thereafter:

(i) A potential seller informs on the website of MA the characteristics of his property (location, size, number of rooms, etc..). He may also provide additional information on his motives to sell and his preferred selling price;

(ii) MA asks two or three real estate agents to visit the property and estimate its market price.

(iii) A negotiation process is initiated with the client, which may lead to the assignment of sales mandates to none, one or the other of the two agents, or both;

(iv) If at least one mandate has been given, a sales process is initiated, starting from the listing price established at the previous step;

(v) If a sale occurs, fees are divided accordingly between the real estate agents and MA.

The negotiation phase at the third step can take two different forms. Regarding the Liberty process which serves here as the main benchmark, the seller bargains directly and independently with each real estate agents: after the visit of the agents, they inform MA of their estimate of the housing value but each agent then negotiates independently with the seller to agree on a listing price and possibly obtain a sales mandate. On the other hand, in the historical offer Serenity, MA collects housing estimates sent by the brokers, then bargains with the seller in order to fix a listing price. In case an agreement is reached with the seller, an identical sales mandate is given to agents. Thus, those two processes mainly differ by the degree of competition during steps (ii) and (iii) :

competition between agents in Liberty, full collusion with delegation to a third party negotiator in Serenity.

During step (iv), real estate agents are competing in order to find buyers and sell the property. There is a significant difference at this level between the two previously mentioned processes. In Serenity, similar exclusive mandates are given (i.e. with the same listing price), so that there are always two and only two real estate agents competing frontally (as detailed in the next section, the Serenity process is analyzed over a period during which the number of agents is limited to two). In Liberty, only one of the agents is selected in 75% of the cases that result in a sales process, but the seller can also decide to give a non-exclusive mandate and sign sales mandates with other real estate agents.[10] Unfortunately, we observe only partly and indirectly if this is the case in the data (this information is not observed by MA, but the seller indicates if he has already started to market his property), so we cannot rule out cases where the sales process put in place suffers from a lack of competition between agents. Therefore, it is not easy to rank in a robust manner the two processes in terms of competition during stage (iv), even if the competitive pressure seems in most cases stronger in Serenity.[11]

Descriptive statistics and sources of variation in competition

We rely on a sample of initially 9.127 flats in Paris. Their values have been estimated between 2013 and 2019. Among these housing units, we observe a listing price in approximately 42% of cases and a selling price in 24% of cases. [12] The two following maps show

[10]Moreover, if the seller is disappointed with the agent he contracted with, nothing prevents her from signing another mandate with the agent he initially rejected.

[11]Besides, there is also a slight difference regarding fees. On average, the buyer pays a commission equal to 5% of the value of the property at step (v). In the case of Liberty, the real estate agent gets the commission and pays back some to MA. In the case of Serenity, the commission is shared between MA and the agent which found the buyer, while the other agent obtains a small compensation (mainly, a refunding of administrative costs).

[12]This corresponds to a success rate of 54% of the sales process intermediated by MA. This rate is quite low, which is explained by the fact that only part of the mandates are exclusive. The success rate of those exclusive mandates is about 70%, close to what is observed on average in French real estate

how these dwellings are geographically dispersed in Paris. We observe housing units in almost all areas in Paris even if some zones seem under-represented (especially the zone between the "Place de la Concorde", "Place Roosevelt" and the "Invalides" which are the most expensive areas in Paris). In these maps, we divided the sample in function of the quantiles of the "price per square meters". Darker points indicate higher prices.

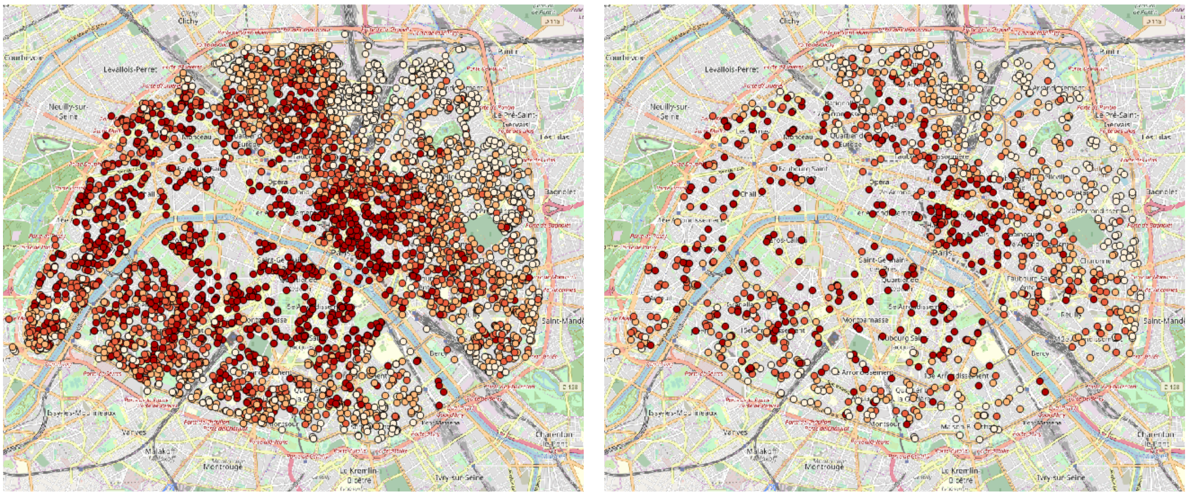


Figure 1: Housing units whose value has been estimated by a real estate brokers (left) and sold properties (right).

We are interested in measuring the impact of competition between real estate agents on the estimated values of properties they give to sellers. Our main source of variations is the number of agents put in competition on a given sale by MA in the Liberty process. The company decided in 2016 to increase the number of agents to three on a local basis, once the online company was able to contract locally with a third broker, thus strengthening competition. The possibility of a local bias can not be ruled out, i.e. the acquisition of a third agent may be determined by the local characteristics of the market (for example it may be easier in a denser area, or harder if some local brokers are not willing to cooperate with MA). As detailed in section 3.3 , our empirical strategy takes this possibility into account.

Two other sources of variation are used to test the effect of competition:

- *Comparison between Serenity and Liberty:* This amounts to compare compare sys-

brokerage. The success rate of non-exclusive mandate is almost two times lower. The sale process is studied more in detail in section 4.2

tematic collusion between agents (through the delegation to a single representative) versus organized competition between two agents. The main potential bias regarding this source of variation comes from the fact that the sellers select upstream which process will be used. This will be discussed in detail in section 3.3. Also, as mentioned in the previous section, it is not easy to rank in a robust manner the two processes in terms of competition during stage (iv) once the mandates are signed. As we will see later, this is not a problem for the econometric tests carried out later in this paper, in which we focus primarily on the three first steps.

- *Potential collusion during interaction between agents:* The ability to communicate and to coordinate is essential for developing collusive behavior. In the theoretical literature, collusion are often considered to appear after repeated interactions. A logical way to test this would be to measure the impact of past interactions between brokers on their estimated prices. However, such a test is fragile since the number of past interactions is endogeneous and since we do not observe the interactions that are not intermediated by MA. We provide this analysis in the appendix, but prefer to rely in the core text on another proxy of collusive behavior. We observe at what time the agents visit the property for sale, and construct a dummy 'close time' that indicates whether they have visited the housing unit in the same time slot of half an hour. This tells us if the real estate brokers could met and coordinate during the visit of the property. In a sense, using this dummy as an explanatory variable for estimated broker's price can be seen as a "reduced form" equation where we would be primarily interested in a "collusion variable" but directly used a an instrument this dummy. [13]

It is difficult to analyze the impact of the timing of visits when there are three agents, because when two agents visit at the same time, the ability to collude is limited if the

[13] It is important to notice that sellers do not have precise information on which agents is competing with them for a given flat (on average, a given broker is put in competition by MA with ten other brokers over the period considered). Thus, visiting at the same time reveals both who the competing broker is and provides a time frame for interacting with it.

third agent is not present. Moreover, as mentioned above, using "Three vs. two agents" as a source of variation in competition corresponds to a specific period. Therefore, we define three specific samples in which we focus on a single source of variation: [14]

- *Three vs. two agents* : data sample covering 2016-2019 for only Liberty (1884 housing units);
- *Liberty vs. Serenity* : data sample covering 2013-2015 (4041 housing units);
- *Time between visits:* : data sample covering 2013-2019 for only Liberty with two agents (3686 housing units).

In the annex, we provide robustness checks by testing simultaneously the three corresponding dummies. Our sample is described in Table 1. It provides means and standard deviations for the main variables. In particular, it provides information on our main dependent variable - the estimated value of properties by real estate agents - as well as hedonic housing characteristics.

Table 1: Descriptive statistics

	Sample 1 (2013-2015)			Sample 2 (2016-2019)			Sample 3 (2013-2019)		
	mean	sd	count	mean	sd	count	mean	sd	count
characteristics									
size (m^2)	56.22	33.257	4041	56.17	31.201	1884	57.50	33.546	3686
nbr rooms	2.57	1.279	4041	2.58	1.222	1884	2.62	1.284	3686
nbr bathrooms	1.10	0.414	4041	1.10	0.411	1884	1.11	0.424	3686
= 1 if housing has a cellar	0.78	0.575	4041	0.78	0.589	1884	0.78	0.579	3686
= 1 if building has an elevator	0.60	0.491	4041	0.59	0.491	1884	0.61	0.488	3686
Age (in decades)	9.22	6.321	3375	9.38	5.412	914	9.34	6.561	2942
seller information									
=1 if seller declares a minimum selling price	0.44	0.497	4041	0.12	0.321	1884	0.39	0.489	3686
=1 if seller declares an ideal selling price	0.47	0.499	4041	0.12	0.322	1884	0.42	0.493	3686
=1 if seller declares a motivation to sell	0.99	0.089	4041	0.84	0.367	1884	0.97	0.161	3686
=1 if selling process already	0.17	0.377	4041	0.12	0.326	1884	0.14	0.347	3686
coordination and competition									
=1 if serenite offer	0.23	0.421	4041	0.00	0.000	1884	0.00	0.000	3686
=1 if agents visit within a close period	0.09	0.282	4041	0.04	0.192	1232	0.08	0.265	3527
=1 if three agents visit the flat	0.00	0.000	4041	0.70	0.460	1884	0.00	0.000	3686
evaluation and prices									
average estimated value (in thousands euros)	464.79	305.773	4041	520.13	325.880	1884	487.29	316.664	3686
(initial) listing price (in thousands euros)	468.18	306.250	1711	531.66	338.076	553	497.05	319.300	1441
selling price (in thousands euros)	394.61	261.383	976	479.02	290.564	297	424.42	278.740	712

Notes: This tables uses data on housing units on the Parisian real estate markets between 2013 and 2019.

[14] In the following, we also explore whether these sources of variation in competition overlap.

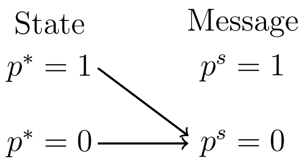
3 Empirical analysis of housing valuation by brokers

3.1 Theoretical predictions

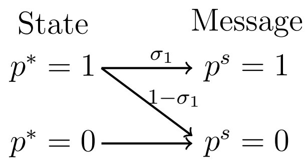
The objective of this empirical work is to estimate the impact of competition on the quality of information provided by real estate brokers to their clients when assessing their property. It is important to notice that this effect in theory may very well be in one way or another. As mentioned in the introduction, theoretical predictions regarding the effect of competition on information transmission are available under some strong assumptions: for instance a positive effect when experts have opposite biases (Krishna and Morgan, 2001), or a negative effect when clients have homogeneous and biased beliefs in a specific direction while experts have no bias (Heidhues and Lagerlöf, 2003). In the context of real estate agents, there are no such specifics that would allow a clear prediction.

We describe thereafter a very schematic model (solved in the appendix) to illustrate and confirm the main underlying economic intuitions. The optimal listing price for the client is assumed to take two distinct values, equal respectively to p_L or p_H with $p_H > p_L$, depending on the quality of his house. The client would lose money by selling a high quality house at a low price, while he would lose too much time by selling a low quality house at a high price (or even be forced to lower his price later). Brokers observe the exact price p^* of the house, and propose a listing price equal either to p_L or p_H as a take it or leave it offer. Clients have an initial belief, i.e. a probability that $p^* = p_H$ distributed uniformly on the interval $[0, 1]$. They update their beliefs when receiving an offer, and can either accept or reject it. In this latter case, they sell on their own with an additional cost c that reflects the time and effort required to directly manage the sales process.

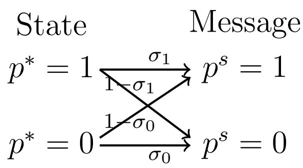
When there is only one broker, we prove in the annex that he chooses to always propose low listing price p_L when the client is sufficiently captive (high c). Otherwise, he chooses a mixed strategy and reveals that $p^* = p_H$ with some positive probability $\sigma_1 < 1$. Those two strategies denoted respectively (AL) and (DB) are described in the picture thereafter. Increasing competition by adding a second broker can either increase or decrease price revelation. Indeed, competitive pressure may induce a broker to reveal a high price (for fear of losing the client) or not reveal that a house is of poor quality (in order to attract a client). Another equilibrium may occur in that case, a mixed equilibria (DU) in which brokers only partially reveal the real price, both when $p^* = p_H$ and $p^* = p_L$.



Always Low (AL)



Downward Bias (DB)



Downward & Upward bias (DU)

It is easy to see that, for the client, there is a clear ranking of the first two strategies $(DB) \succ (AL)$, whereas the ranking of the strategy (DU) depends on how far the brokers try to please customers by valuing excessively their properties (i.e. the probability $1 - \sigma_0$ of lying when $p^* = 0$). With a slight abuse of language, we refer to this last strategy as *pandering*. We show in the appendix that adding one broker may either improve or degrade information transmission, depending on the cost c and on the financial stakes for the brokers. This model is too simple to be calibrated on real data and used to provide predictions regarding the case analyzed thereafter. Instead, we settle this question empirically in the case of Parisian real estate agents by clearly showing that competition benefits customers. More precisely, we show that competition induces brokers to raise their real estate evaluation (section 3.4), that this is only partly explained by a pandering strategy (section 4.1), and that the overall effect for clients is positive, with higher sale prices without significantly longer time on the market (section 4.2).

3.2 Empirical Methods

To analyze whether the degree of competition for new mandates affects the estimations of housing values by real estate brokers, we estimate variants of the following equation with different sets of controls and fixed effects.

$$\text{Estimated value}_{ijat} = \text{Competition}_i^{\alpha}\, \boldsymbol{\beta} + \mathrm{X}_i\, \boldsymbol{\gamma} + \mu_a + \mu_t + \mu_j + \epsilon_{iat} \tag{1}$$

where Estimated value_{ijat} indicates the log estimated value of property i that is located in "district" a and is estimated by the real estate agency j during the "year-month" t. We use the logarithm of the estimated values in the regression as it is often the case in hedonic price analysis. As mentioned before, we first test the three sources of variation separately, i.e. the "competition" variable is a dummy that corresponds successively to the three different changes in the level of competition : (A) move from Liberty to Serenity, (B) increase in the number of agents from 2 to 3 and (C) the agents visit at the same time the house for sale. More precisely, the variable Competition^C is a dummy which takes the value one when both real estate agents visit the property during a same short time window of 30 minutes, and one otherwise. The variable Competition^A (resp. Competition^B) are respectively dummies that takes the value of one if the chosen process is Serenity (resp. if three agents visit the house). Thus, a value equal to one reflects an increase in the possibilities of collusion in cases A and C, whereas it reflects an increase of competition in case B.

The variable μ_a, μ_t and μ_j are the corresponding geographic, time and "real estate agency" fixed effects while ϵ_{iat} is an error term clustered at the "housing" level. The vector X includes three different sets of control variables:

- *hedonic housing characteristics*: it should be noted that our data cover not houses, but apartments, which are by nature more homogeneous goods. Nevertheless, we control for the size (in square meters) of propertied, distinguishing the case where it is less than 50 m2 (because the market for smaller apartments is more expensive). We also control for number of rooms, number of bathrooms, on which floor is the apartment, whether the property has a cellar and whether the building has an elevator. All these information are included within the regression using sets of dummy variables. We also control for the age of the building adding one dummy variable per decade.

- *sellers' characteristics*: In order to limit the possibility that our results are driven by differences among clients, we include dummy variables which indicate whether sellers declared a minimum or an ideal price to *MA*, and include as well a set of dummy variables that controls for "reasons to sell" (need of more space, need of cash, divorce, etc.) declared by sellers at step (i) when accessing the MA website. In total, thirteen dummies allow us to control some of the heterogeneity between sellers that can influence bargaining.

- *real estate brokers' visit*: we include variables reflecting visiting time (day and visiting hours), as well as an "Experience" variable indicating the (log) number of times the real estate agent has estimated housing values up to date t. It aims to capture if the agent is used to working with MA.

- *external competition*: We include a binary variable that indicates whether the seller said if he has already started the marketing process (sellers do not specify whether they did that alone by posting an ad, or by contacting an external broker).

3.3 Robustness of the identification strategy

Our identification assumptions are that the competition variables are uncorrelated with unobserved elements that also affect estimation of housing values. Three possible endogeneity biases threaten these asssumptions, concerning respectively the strategy of brokers, the characteristics of flats, and preferences of sellers.

(a) *Potential endogeneity of brokers' strategies and of the competition level*: our main specification includes real estate agency fixed effects and we therefore compare how the same real estate agency changes its behavior when competition changes. Besides, it includes also time and geographical fixed effects (i.e. years, months and local districts). This is all the more important for the first source of variation, since the timing of the acquisition of a third agent may be determined by the local characteristics of the market, and that agents acquired more recently by MA may follow a slightly different strategy than older brokers working with the internet company.

(b) *Potential endogeneity of unobserved characteristics of flats*: As mentioned in the previous section, we control for characteristics of flats using a wide variety of control variables. Besides, our empirical analysis is limited to apartments, which exhibits a lower heterogeneity than dwellings. The R-squared in our hedonic regressions is quite high which seems to indicate that we are not omitting important explanatory variables. This is reassuring but not sufficient to guarantee the absence of potential bias. A strategy often used in the real estate literature in order to control for unobserved housing characteristics is to take advantage of the houses that are sold several times. We cannot use this "repeated sells" strategy as we never observe the same flat being sold several times. However, in a robustness check provided in the annex (figure 10), we inspire from it and are able to re-estimate our main specification using the flats whose owner revealed to MA the price she paid when she bought it. While adding this variable severely restrict the sample size (it is observed in approximately one third of cases), it allows us to control for unobserved characteristics that are reflected in the buying price. This strategy leads to similar results and support our main findings even though, the reduced sample size make some of the estimates not statistically significant.

(c) *Potential selection bias of sellers*: this is the most tricky point, which primarily concerns the second source of variation, as Sellers may sort between Liberty and Serenity offers based on unobserved characteristics. The control of sellers characteristics should limit this problem. Besides we are able to replicate the main results using only properties whose owner accepted to sign a contract with at least one real estate agent affiliated to MA (table 6). This allows to check that our results are not influenced by a self-selection bias induced by clients who enroll in this process without really wanting to go all the way

This potential bias can also affect the third source of variation as clients may accept that agents to visit at the same time based on unobserved characteristics (for instance, clients in a hurry to sell or that has limited time to allow visit). As mentioned in section 2.1, collusion occurs may also occur as a result of repeated interactions. We provide in the annex a similar test using the number of past interactions between agents as an indicator of potential collusions. The results (table 11) are statistically significant and quite similar: when the number of past interactions between the two brokers is in the top decile (18 on average) instead of the median (4 interactions), the estimated prices are 2% lower.

Lastly, regarding the first source of variations, it is important to notice, as mentioned in section 2.1, that the explanatory variable is the number of real estate agents selected by MA. It may be that in the end the three agents do not all make visits, for example because the client finally gives up granting a third appointment to the last agent, but this choice does not bias our estimate. In other words, we estimate the impact on agent behavior of the selection of the number of agents made upstream, a source of variation that is exogenous to seller's characteristics.

We acknowledge that those robustness tests and complementary checks does not rule out completely the potential endogeneity problems regarding the second and the third source of variation. However, we believe that the first source of variation provide robust results, as the potential sources of endogeneity are well controlled by the strategies presented previously. Finally, the fact that the multiple source of variations lead to the same conclusion confirms the robustness of the overall result presented in this work.

3.4 Results

As shown in table 2, all models converge to say that the possibilities of collusion (resp. strenghtening of competition) lead real estate agents to lower (resp. increase) their estimates of the housing value of their potential customers. When the number of agents is fixed and equal to 2 (first column), the value of a property estimated under the collusive process (Serenity) is 5.6% lower than the one of a similar property estimated under the competitive one (Liberty). Under the competitive process Liberty, these estimations increase by 2.7% when the number of agents rises up to 3 (second column). Lastly, when we restrict ourselves to the Liberty process with two agents, their estimated values are 3.1% lower when both real estate brokers visit the property within the same time window of less than half an hour. In order to insure that our results are robust to variation of the specification, robustness checks are presented in the online appendix. We use smaller geographic zone fixed effects (table 7) and then we modify the level of clustering of the error terms (table 8). In all those additional tests, we obtain similar significant coefficients.

Table 2: main results

	The dependent variable is the (log) estimated value		
	(1) Serenite (2013-2015)	(2) Three evaluations (2016-2019)	(3) Close moment (2013-2019)
Coordination variable			
=1 if serenite offer	-0.056*** (0.006)		
=1 if three agents visit the flat		0.027*** (0.009)	
=1 if agents visit within a close period			-0.031*** (0.011)
Housing characteristics			
size (square meters)	0.009*** (0.001)	0.010*** (0.000)	0.009*** (0.001)
small housing unit: size $\leq$ 50sq.m	-1.178*** (0.040)	-1.149*** (0.049)	-1.189*** (0.047)
size $\times$ small housing unit	0.024*** (0.001)	0.024*** (0.001)	0.024*** (0.001)
Agent characteristics			
experience	-0.001 (0.005)	-0.011 (0.010)	-0.002 (0.005)
Seller characteristics			
=1 if seller declares a minimum selling price	0.006 (0.006)	0.017 (0.015)	0.007 (0.007)
=1 if seller declares an ideal selling price	0.002 (0.006)	0.001 (0.016)	0.003 (0.007)
selling process already started	-0.004 (0.008)	0.008 (0.012)	-0.003 (0.009)
Real estate agency fixed effects are included	Yes	Yes	Yes
Zipcode fixed effects are included	Yes	Yes	Yes
Year-month fixed effects are included	Yes	Yes	Yes
Day of week and hours dummies are included	Yes	Yes	Yes
Seller controls are included	Yes	Yes	Yes
Housing controls	Yes	Yes	Yes
Obs	7176	2881	5898
R2	0.923	0.938	0.919

Notes: This tables uses data on housing units on the Parisian real estate markets between 2013 and 2019. There are three samples based on the 2013-2015 data, the 2016-2019 data (Liberty offer only) and the 2013-2019 data (Liberty offer only). The dependent variable is the estimated value of the housing unit according to the real estate agent. Standard errors clustered at the housing unit level are presented in parenthesis. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

There may be interactions between these effects, with potential cumulative impacts. This is confirmed by the analysis presented in table 9 provided in the appendix, which looks at the simultaneous effects of the sources of variation over two distinct periods. Accordingly, these effects add up at least partially, and the downward evaluation bias may exceed 10% when the evaluations are conducted under the serenity process by agents who cross each other during the assessment visits, in comparison with those conducted by three agents competing in the freedom process. Besides, the first column in table 9 shows that there is no interaction between the two first sources of variation in competition, which means that there is a similar effect under the Serenity process when both real estate brokers visit the property within the same time window of less than half an hour. This can be explained by the fact that MA generally chooses a value between the two brokers' evaluations and that, when meeting during the evaluation visits, they have the ability to collude in order to both propose a lower evaluation. [15]

All these results confirm, as discussed in the introduction, that real estate agents reduce their estimation of the property of their potential customers when they do not face a strong competitive pressures for new listings. The result is all the more striking that we obtain a similar order of magnitude, but with the opposite sign, to that obtained by the articles of Rutherford et al. (2005) and Levitt and Syverson (2008) mentioned above. It is as if putting competition explicitly between agents, upstream of the negotiation with their clients, led them to advise to sell at the price they would have chosen if the property belonged to them! Of course, this is an average result, which can hide the fact that in some cases competition leads agents to offer abnormally high prices to capture their customers. As shown in Section 4, this is not the dominant behavior, and this type of competitive pressure benefits on average to the customer.

4 Interpretation and impact on customer's welfare

The impact of the competition observed in the previous section can give rise to two different types of explanation. First, this may result from an overall improvement in the quality of information exchanged between agents and their clients, as competition prevents brokers from skewing their estimates downward. Secondly, it may reflect an excessive pandering if agents bias their estimate upwards in order to capture clients. The consequences for the clients are very different. In particular, in the latter case, the selling

[15]There is no such effect in the second column, which look at the interaction between the type of process and the number of agents because there are very few cases with three agents in the Serenity process.

process would be deteriorated, i.e. the clients would not sell their real estate quickly and could be brought to lower their sale price to be able to sell. Besides, excessive pandering can result in a more complex mechanism of "bunching", when brokers align their estimation on the price quoted by the client. In what follows, we first examine if and how agents bunch their estimate on the preferred price given by the seller (if any), then analyze the whole subsequent sales process.

4.1 Pandering to client's wish

As explained above, sellers sometimes provide an *ideal* selling price to MA. In this case, real estate brokers may decide to provide a housing estimate that is exactly equal to this ideal price. With a slight abuse of language, we refer to this situation as *pandering*. It is a relatively common strategy: it happens in approximately 7.5% of cases where the seller indicates an *ideal* price, as shown in figure 3 where we plot the histogram of the ratio between brokers' evaluations and ideal prices declared by the sellers. The mass at one is generated by the agents who exactly confirm the ideal prices of the sellers. This is not just a story of convenience rounding. Indeed, the mass of observation detected in figure 2 seems to be more important than the number of "missing" observations near the mass. This is checked more carefully in the appendix by computing the residual of a polynomial approximation of the density. [16]

Pandering can happen when the client suggests an abnormally low price - which suits the agent who want to sell as soon as possible, or when the agent is ready to please a customer by agreeing to start selling at the high price indicated by the client. As shown in table 3a, this occurs mainly in the latter cas as pandering is associated to higher prices on average, but this strategy does not explain what was observed in the previous section: the significance and the coefficients attached to the effects of the competition remain similar when we add in the regression a variable equal to one when the agent's estimate is exactly equal to the client's ideal price. However, as shown in table 3b, this is part of the strategy of agents when moving from the collusive process of Serenity to Liberty.

[16] Pope et al. (2015) use a close strategy while studying real-estate selling prices.

Table 3: Pandering

(a) Impact of pandering to client's wishes.

	The dependent variable is the (log) estimated value		
	(1) Serenite (2013-2015)	(2) Three evaluations (2016-2019)	(3) Close moment (2013-2019)
Coordination variable			
=1 if serenite offer	-0.055*** (0.006)		
=1 if three agents visit the flat		0.027*** (0.009)	
=1 if agents visit within a close period			-0.031*** (0.011)
Pandering			
= 1 if agent panders	0.025** (0.010)	0.020 (0.035)	0.030*** (0.010)
Housing characteristics			
size (square meters)	0.009*** (0.001)	0.010*** (0.000)	0.009*** (0.001)
small housing unit: size $\leq$ 50sq.m	-1.178*** (0.040)	-1.149*** (0.049)	-1.189*** (0.047)
size $\times$ small housing unit	0.024*** (0.001)	0.024*** (0.001)	0.024*** (0.001)
Agent characteristics			
experience	-0.000 (0.005)	-0.011 (0.010)	-0.001 (0.005)
Seller characteristics			
=1 if seller declares a minimum selling price	0.006 (0.006)	0.017 (0.015)	0.007 (0.007)
=1 if seller declares an ideal selling price	-0.000 (0.006)	-0.000 (0.017)	0.000 (0.007)
selling process already started	-0.004 (0.008)	0.007 (0.012)	-0.003 (0.009)
Real estate agency fixed effects are included	Yes	Yes	Yes
Zipcode fixed effects are included	Yes	Yes	Yes
Year-month fixed effects are included	Yes	Yes	Yes
Day of week and hours dummies are included	Yes	Yes	Yes
Seller controls are included	Yes	Yes	Yes
Housing controls	Yes	Yes	Yes
Obs	7178	2881	5898
R2	0.923	0.938	0.919

(b) Impact of competition and collusion on pandering.

	The dependent variable is a dummy indicating that the agent panders		
	(1) Serenite (2013-2015)	(2) Three evaluations (2016-2019)	(3) Close moment (2013-2019)
Coordination variable			
=1 if serenite offer	-0.050*** (0.010)		
=1 if three agents visit the flat		0.003 (0.104)	
=1 if agents visit within a close period			-0.010 (0.028)
Housing characteristics			
size (square meters)	-0.000 (0.000)	0.001 (0.006)	-0.000 (0.001)
small housing unit: size $\leq$ 50sq.m	0.028 (0.051)	-0.046 (0.487)	0.004 (0.064)
size $\times$ small housing unit	-0.000 (0.001)	0.004 (0.011)	0.001 (0.001)
Agent characteristics			
experience	-0.007 (0.012)	0.004 (0.158)	-0.007 (0.014)
Seller characteristics			
=1 if seller declares a minimum selling price	-0.018* (0.011)	-0.037 (0.133)	-0.020 (0.014)
selling process already started	0.008 (0.014)	-0.018 (0.112)	0.006 (0.018)
Real estate agency fixed effects are included	Yes	Yes	Yes
Zipcode fixed effects are included	Yes	Yes	Yes
Year-month fixed effects are included	Yes	Yes	Yes
Day of week and hours dummies are included	Yes	Yes	Yes
Seller controls are included	Yes	Yes	Yes
Housing controls	Yes	Yes	Yes
Obs	3434	341	2621
R2	0.138	0.793	0.187

Notes: This tables uses data on housing units on the Parisian real estate markets between 2013 and 2019. There are three samples based on the 2013-2015 data, the 2016-2019 data (Liberty offer only) and the 2013-2019 data (Liberty offer only). The dependent variable differs in each panel. In panel (a) it is the estimated value of the housing unit according to the real estate agent. In panel (b), it is whether the agent panders to the customer, that is, estimates the housing unit value at the ideal price declared by the seller. Standard errors clustered at the housing unit level are presented in parenthesis. In this model, due to the large number of binary variables and fixed effects, we use a linear probability model. As this model has limitations, we check that we get similar results with a simpler logit model (which has the drawback of being able to suggest more bunching when three agents are in competition). * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

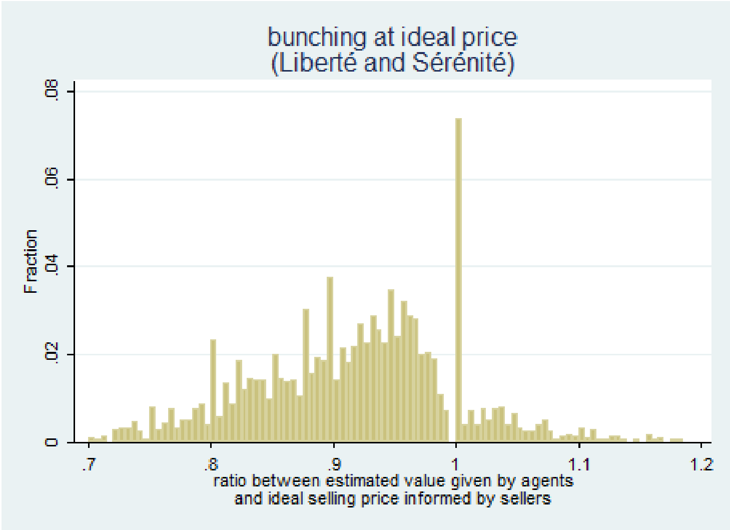


Figure 2: Number of observations per values of the ratio between the estimated value (by real estate agents) and the ideal price (logarithmic scale on the y-axis on the right).

4.2 Time on the market and selling price

In this subsection, we analyze whether the previous differences in estimated values affect the subsequent sale of properties, in order to understand what is the overall impact for the customers. In order to do so, we first replicate the previous estimations using as dependent variables the "initial listing price" and the "selling price" of properties. [17] As shown in table 4, there is a similar effect of competition and collusion on listing and selling prices. It is as if the effects on estimated prices were maintained throughout the sales process. The orders of magnitude and the significance are similar, except regarding the impact on the selling price of the shift from 2 to 3 agents, but the data are scarce in that case (less than 500 observations).

It remains to see whether these higher selling prices are obtained with as counterpart

[17] Sometimes, we observe two initial listing prices. This is the case in the Liberty offer when the two agents obtain a mandate and that the seller chooses a different listing prices with the two agents. This does not affect significantly our results. In the data presented here, in these specific cases we use the average value of the two listing prices, and remove the real estate agency fixed effects and the "experience" variable as we do not observe which agent obtained the mandate in the Liberty offer. If instead we simply remove those observations from the econometric analysis, results remain unchanged with the same degree of significance.

a longer selling time. We analyze the impact of our ”competition” variables on the time on the market (TOM) using both a classical OLS and a survival analysis, with each methods having its pro and cons (results examined thereafter are obtained in a convergent manner using the two methods). [18] The interpretation of such analysis is complicated by the fact that competitive changes upstream of the process may also be correlated with downstream changes in competition. For that reason, we exclude here the analysis of the impact of ”serenité” which is discussed in the appendix. [19] As shown in table 5, the shift from 2 to 3 agents leads to a lower TOM even when we control by the number of given mandates: the mere fact that the client has been in contact with two other agents seems to be enough to put pressure on the broker who hurries to sell. On the other hand, the fact that the two agents collude during the visit of the property has no significant impact on the TOM. [20]

This shows that the impact of competition observed in the previous section result from an overall improvement in the quality of information exchanged between agents and their clients. Competition prevents brokers from skewing their estimates downward, thus benefits to sellers by driving sales at higher prices without slowing down the process.

[18] While the OLS uses information only from those observations where we observe a sale, the survival analysis relies on more observations. However, the estimation procedure does not converge in the survival analysis if we use all the explanatory variables. We then estimate a simpler model (with in particular years instead of year-month fixed effects).

[19] As previously mentioned, in Serenity, two brokers are always competing frontally during the sale process so that, according to MA, the competitive pressure is higher in that case.

[20] Results presented in table 5 take into account non-exclusive mandates, whose flats can be sold outside the process supervised by MA. However, the impact of non-observed sales in not the same when using OLS and duration models. The latter simply consider that such flats have not been sold during the period of observation, whereas the former use only information on sells realized by MA agents. We provide in the annex a similar analysis restricted to exclusive mandates (cf. table 15). The results are less significant but similar.

Table 4: Listing and selling prices

	The dependent variable is					
	(1) listing price	(2) selling price	(3) listing price	(4) selling price	(5) listing price	(6) selling price
sample:	Serenite (2013-2015)	Serenite (2013-2015)	Three evaluations (2016-2019)	Three evaluations (2016-2019)	Close moment (2013-2019)	Close moment (2013-2019)
Coordination variable						
=1 if serenite offer	-0.042*** (0.008)	-0.052*** (0.014)				
=1 if three agents visit the flat			0.051*** (0.015)	0.026 (0.025)		
=1 if agents visit within a close period					-0.044* (0.021)	-0.092* (0.051)
All mandates are exclusive	-0.005 (0.010)	-0.014 (0.017)	-0.008 (0.015)	0.001 (0.038)	-0.003 (0.012)	-0.010 (0.022)
Housing characteristics						
size (square meters)	0.012*** (0.001)	0.012*** (0.001)	0.011*** (0.001)	0.011*** (0.002)	0.011*** (0.001)	0.011*** (0.001)
small housing unit: size $\leq$ 50sq.m	-1.055*** (0.056)	-0.939*** (0.062)	-1.159*** (0.060)	-1.040*** (0.095)	-1.066*** (0.049)	-0.976*** (0.088)
size $\times$ small housing unit	0.022*** (0.001)	0.020*** (0.001)	0.024*** (0.001)	0.021*** (0.002)	0.022*** (0.001)	0.021*** (0.002)
Seller characteristics						
=1 if seller declares a minimum selling price	-0.000 (0.011)	0.004 (0.019)	0.011 (0.028)	0.029 (0.069)	-0.002 (0.008)	-0.007 (0.022)
=1 if seller declares an ideal selling price	0.009 (0.009)	0.018 (0.013)	0.000 (0.027)	-0.028 (0.059)	-0.006 (0.010)	0.011 (0.026)
selling process already started	0.004 (0.012)	-0.001 (0.018)	0.001 (0.021)	0.020 (0.047)	0.008 (0.015)	-0.002 (0.024)
Zipcode fixed effects are included	Yes	Yes	Yes	Yes	Yes	Yes
Year-month fixed effects are included	Yes	Yes	Yes	Yes	Yes	Yes
Seller controls are included	Yes	Yes	Yes	Yes	Yes	Yes
Housing controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1618	896	826	437	1317	625
R2	0.923	0.925	0.937	0.906	0.924	0.919

Notes: This tables uses data on housing units on the Parisian real estate markets between 2013 and 2019. There are three samples based on the 2013-2015 data, the 2016-2019 data (Liberty offer only) and the 2013-2019 data (Liberty offer only). The dependent variable are the (log) listing price and the (log) selling price. Standard errors clustered at the housing unit level are presented in parenthesis. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

Table 5: Time to sell - survival analysis

	Analysis of the TOM					
	(1) OLS	(2) Weibull	(3) Cox model	(4) OLS	(5) Weibull	(6) Cox model
sample:	Three evaluations (2016-2019)	Three evaluations (2016-2019)	Three evaluations (2016-2019)	Close moment (2013-2019)	Close moment (2013-2019)	Close moment (2013-2019)
Coordination variable						
=1 if three agents visit the flat	-0.196* (0.112)	0.330** (0.151)	0.314** (0.149)			
=1 if agents visit within a close period				-0.034 (0.156)	-0.028 (0.166)	-0.076 (0.165)
All mandates are exclusive	0.103 (0.121)	1.143*** (0.193)	1.050*** (0.189)	-0.050 (0.119)	1.065*** (0.101)	0.984*** (0.099)
Housing characteristics						
size (square meters)	0.012** (0.005)	-0.002 (0.006)	-0.001 (0.005)	-0.003 (0.003)	-0.010* (0.005)	-0.011** (0.005)
small housing unit: size $\leq$ 50sq.m	0.442 (0.400)	-0.053 (0.619)	-0.101 (0.611)	-0.996** (0.443)	0.421 (0.463)	0.480 (0.461)
size $\times$ small housing unit	0.002 (0.007)	0.002 (0.013)	0.002 (0.013)	0.011 (0.008)	-0.001 (0.010)	-0.004 (0.009)
Seller characteristics						
=1 if seller declares a minimum selling price	-0.174 (0.223)	-0.018 (0.249)	-0.038 (0.249)	0.145 (0.105)	-0.150 (0.112)	-0.109 (0.111)
=1 if seller declares an ideal selling price	-0.089 (0.258)	0.055 (0.255)	0.043 (0.255)	-0.084 (0.173)	0.073 (0.113)	0.049 (0.111)
selling process already started	-0.236 (0.146)	0.113 (0.222)	0.088 (0.220)	-0.132 (0.091)	0.153 (0.134)	0.155 (0.133)
Zipcode controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	No	Yes	Yes	No	Yes	Yes
Year-months controls	Yes	No	No	Yes	No	No
Seller controls are included	Yes	Yes	Yes	Yes	Yes	Yes
Housing controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	319	471	471	580	1200	1200

Notes: This tables uses data on housing units on the Parisian real estate markets between 2013 and 2019. We report three specifications in two different samples (2016-2019 and 2013-2019). In all cases, the sample is limited to housing units where we observe a listing price. The estimated models are (1) OLS analysis of the time on market and survival-time models that assume Weibull distributions (2) as well as the Cox proportional hazard models (3). Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$. We report the coefficients of the model.
Lecture: in the OLS model, a positive sign indicates a longer time on the market whereas in the survival-time models, a positive sign indicates that the hazard rate increases and therefore that the duration decreases.

5 Conclusion

In this paper, we use data from an online broker to show that competition can counter the tendency of real estate brokers to underestimate properties they are supposed to sell on behalf of their clients (Rutherford et al., 2005; Levitt and Syverson, 2008). The result is all the more striking as we obtain an order of magnitude similar to that obtained by previous empirical works that estimated the undervaluation of property in comparison to property owned by brokers. This is as if increased competitive pressure during the mandate acquisition phase was enough to prevent on average the distorsion of information by experts. Competition ends up being beneficial to the clients, since selling prices are significantly higher while time on the market is not significantly affected.

To our knowledge, this is the first time that an empirical analysis is conducted as far upstream of such a negotiation process between an expert and his client. This allows us to further analyze brokers' strategy, in particular to see to what extent they pander to client's wishes by aligning evaluations on desired prices. We acknowledge potential limitations in this analysis, due in particular to potential endogeneity problems as the negotiation process is largely left to clients whose preferences remain unobserved. Yet, the use of multiple control variables and the fact that using different sources of variation in competition - including a "visit time window" less sensitive to endogeneity bias - lead to the same conclusions support the robustness of our results.

As illustrated by a simple model discussed in the core text and detailed in the appendix, the impact of competition on information transmission is a priori ambiguous. Our work shows a positive effect in the context of real estate transactions but further research is needed to analyze this more deeply both theoretically and empirically in other contexts. This seems all the more important as direct transactions between individuals develop strongly with the advent of Internet, with frequent recourse to a third party to manage the sale or carry out an expertise.

References

Agarwal, S., Ben-David, I., and Yao, V. (2015). Collateral valuation and borrower financial constraints: Evidence from the residential real estate market. *Management Science*, 61(9):2220–2240.

Alonso, R. and Matouschek, N. (2008). Optimal delegation. *The Review of Economic Studies*, 75(1):259–293.

Bolton, P., Freixas, X., and Shapiro, J. (2012). The credit ratings game. *The Journal of Finance*, 67(1):85–111.

Che, Y.-K., Dessein, W., and Kartik, N. (2013). Pandering to persuade. *American Economic Review*, 103(1):47–79.

Conklin, J., Coulson, N. E., Diop, M., and Le, T. (2019). Competition and appraisal inflation. *The Journal of Real Estate Finance and Economics*.

Crawford, V. and Sobel, J. (1982). Strategic information transmission. *Econometrica*, 50(6):1431–51.

Cummins, J. G. and Nyman, I. (2005). The dark side of competitive pressure. *RAND Journal of Economics*, pages 361–377.

Evans, R. G. (1974). Supplier-induced demand: some empirical evidence and implications. In *The economics of health and medical care*, pages 162–173. Springer.

Flynn, S. and Ghent, A. (2017). Competition and credit ratings after the fall. *Management Science*, 64(4):1672–1692.

Gentzkow, M. and Kamenica, E. (2016). Competition in persuasion. *The Review of Economic Studies*, 84(1):300–322.

Gilligan, T. W. and Krehbiel, K. (1989). Asymmetric information and legislative rules with a heterogeneous committee. *American Journal of Political Science*, pages 459–490.

Hackethal, A., Haliassos, M., and Jappelli, T. (2012). Financial advisors: A case of babysitters? *Journal of Banking & Finance*, 36(2):509–524.

Heidhues, P. and Lagerlöf, J. (2003). Hiding information in electoral competition. *Games and Economic Behavior*, 42(1):48–74.

Hubbard, T. N. (1998). An empirical examination of moral hazard in the vehicle inspection market. *The RAND Journal of Economics*, pages 406–426.

Hubbard, T. N. (2002). How do consumers motivate experts? reputational incentives in an auto repair market. *The Journal of Law and Economics*, 45(2):437–468.

Krishna, V. and Morgan, J. (2001). A model of expertise. *The Quarterly Journal of Economics*, 116(2):747–775.

Levitt, S. D. and Syverson, C. (2008). Market distortions when agents are better informed: The value of information in real estate transactions. *The Review of Economics and Statistics*, 90(4):599–611.

Pope, D. G., Pope, J. C., and Sydnor, J. R. (2015). Focal points and bargaining in housing markets. *Games and Economic Behavior*, 93:89–107.

Rochet, J.-C. and Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the european economic association*, 1(4):990–1029.

Rutherford, R., Springer, T., and Yavas, A. (2005). Conflicts between principals and agents: evidence from residential brokerage. *Journal of Financial Economics*, 76(3):627 – 665.

Schneider, H. S. (2012). Agency problems and reputation in expert services: Evidence from auto repair. *The Journal of Industrial Economics*, 60(3):406–433.

Shi, L. and Tapia, C. (2016). The disciplining effect of concern for referrals: Evidence from real estate agents. *Real Estate Economics*, 44(2):411–461.

6 Additional tables

In this section, we present the robustness checks mentioned in the text.

- Table 6 shows that, when we restrict the sample to housing units that are subsequently listed on the market, we can reproduce similar results as in our main analysis. This serves two goals. It insures that our main results are not driven by an unobserved characteristics of sellers (some of them may not be willing to do the entire selling process). Moreover, it ensures that housing units that are listed and sold are similar to those studied in the first analysis.

- Table 7 reproduces the main regression using "zone" fixed effects instead of "district" fixed effects as geographic controls. Each zone corresponds to the quarter of a district (northeast, southeast, south-west, north-west).

- In Table 8, we also reproduce the main regression but with an alternative clustering of standard errors (at the district level).

- In Table 9, we include variables for several source of variations within the same regression. This shows that the sources of variation used in this article are indeed different.

- In Table 10, we show that controling for the price that sellers paid when they initially bought the house leads to qualitatively similar results, even if the number of observations drastically decrease and therefore, results are not always statistically significant.

- In Table 11, we control for the number of interactions between real estate agencies. This does not alter our main findings. Moreover, this new variable also suggests that collusion through repeated interaction lead to smaller estimated prices.

- In Tables 12 and 13, we reproduce the analysis of pandering behaviors taking into account the minimum prices declared by sellers. As explained in the main text, sellers may declare both a minimum and an ideal price. While it seems intuitive that pandering should mostly concern *ideal* prices, it is possible to replicate our results taking into account both minimum and ideal prices.

- Table 14 presents the results on the TOM for serenity whose interpretation, as explained in the main text, is less obvious due to the difference between serenity and liberty sales processes.

- Table 15 present the TOM analysis when restricting the sample to exclusive mandates.

Table 6: Main results : sample restricted to listings

	The dependent variable is the (log) estimated value		
	(1) Serenite (2013-2015)	(2) Three evaluations (2016-2019)	(3) Close moment (2013-2019)
Coordination variable			
=1 if serenite offer	-0.056*** (0.008)		
=1 if three agents visit the flat		0.047*** (0.017)	
=1 if agents visit within a close period			-0.023 (0.018)
Housing characteristics			
size (square meters)	0.011*** (0.001)	0.010*** (0.001)	0.010*** (0.001)
small housing unit: size $\leq$ 50sq.m	-1.111*** (0.045)	-1.143*** (0.082)	-1.122*** (0.049)
size $\times$ small housing unit	0.023*** (0.001)	0.022*** (0.002)	0.023*** (0.001)
Agent characteristics			
experience	0.001 (0.006)	0.007 (0.019)	-0.001 (0.007)
Seller characteristics			
=1 if seller declares a minimum selling price	0.001 (0.009)	0.015 (0.030)	-0.002 (0.010)
selling process already started	0.001 (0.012)	0.015 (0.023)	0.013 (0.014)
Real estate agency fixed effects are included	Yes	Yes	Yes
Zipcode fixed effects are included	Yes	Yes	Yes
Year-month fixed effects are included	Yes	Yes	Yes
Day of week and hours dummies are included	Yes	Yes	Yes
Seller controls are included	Yes	Yes	Yes
Housing controls	Yes	Yes	Yes
Obs	3153	941	2402
R2	0.951	0.972	0.957

Notes: This tables uses data on housing units on the Parisian real estate markets between 2013 and 2019. There are three samples based on the 2013-2015 data, the 2016-2019 data (Liberty offer only) and the 2013-2019 data (Liberty offer only). The dependent variable is the estimated value of the housing unit according to the real estate agent. Here, we replicate our main results using the sample of housing units where we observe an initial listing price. Standard errors clustered at the district level are presented in parenthesis. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

Table 7: Main results : geographic zones

	The dependent variable is the (log) estimated value		
	(1) Serenite (2013-2015)	(2) Three evaluations (2016-2019)	(3) Close moment (2013-2019)
Coordination variable			
=1 if serenite offer	-0.056*** (0.006)		
=1 if three agents visit the flat		0.026*** (0.009)	
=1 if agents visit within a close period			-0.025** (0.011)
Housing characteristics			
size (square meters)	0.009*** (0.001)	0.010*** (0.001)	0.009*** (0.001)
small housing unit: size $\leq$ 50sq.m	-1.169*** (0.040)	-1.153*** (0.049)	-1.179*** (0.046)
size $\times$ small housing unit	0.024*** (0.001)	0.024*** (0.001)	0.024*** (0.001)
Agent characteristics			
experience	-0.002 (0.005)	-0.010 (0.010)	-0.003 (0.005)
Seller characteristics			
=1 if seller declares a minimum selling price	0.005 (0.006)	0.021 (0.015)	0.007 (0.007)
=1 if seller declares an ideal selling price	0.001 (0.006)	-0.005 (0.017)	0.002 (0.007)
selling process already started	-0.005 (0.008)	0.012 (0.012)	-0.001 (0.009)
Real estate agency fixed effects are included	Yes	Yes	Yes
Geographic zone fixed effects are included	Yes	Yes	Yes
Year-month fixed effects are included	Yes	Yes	Yes
Day of week and hours dummies are included	Yes	Yes	Yes
Seller controls are included	Yes	Yes	Yes
Housing controls	Yes	Yes	Yes
Obs	7176	2881	5898
R2	0.926	0.942	0.923

Notes: This tables uses data on housing units on the Parisian real estate markets between 2013 and 2019. There are three samples based on the 2013-2015 data, the 2016-2019 data (Liberty offer only) and the 2013-2019 data (Liberty offer only). The dependent variable is the estimated value of the housing unit according to the real estate agent. This table uses "zone fixed effects" where zones are defined as one fourth of a district. Standard errors clustered at the housing unit level are presented in parenthesis. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

Table 8: Main results : alternative clustering

	The dependent variable is the (log) estimated value		
	(1) Serenite (2013-2015)	(2) Three evaluations (2016-2019)	(3) Close moment (2013-2019)
Coordination variable			
=1 if serenite offer	-0.056*** (0.006)		
=1 if three agents visit the flat		0.027** (0.010)	
=1 if agents visit within a close period			-0.031*** (0.010)
Housing characteristics			
size (square meters)	0.009*** (0.001)	0.010*** (0.001)	0.009*** (0.001)
small housing unit: size $\leq$ 50sq.m	-1.178*** (0.049)	-1.149*** (0.062)	-1.189*** (0.058)
size $\times$ small housing unit	0.024*** (0.001)	0.024*** (0.001)	0.024*** (0.001)
Agent characteristics			
experience	-0.001 (0.006)	-0.011 (0.010)	-0.002 (0.005)
Seller characteristics			
=1 if seller declares a minimum selling price	0.006 (0.006)	0.017 (0.016)	0.007 (0.008)
=1 if seller declares an ideal selling price	0.002 (0.008)	0.001 (0.015)	0.003 (0.009)
selling process already started	-0.004 (0.008)	0.008 (0.012)	-0.003 (0.009)
Real estate agency fixed effects are included	Yes	Yes	Yes
Zipcode fixed effects are included	Yes	Yes	Yes
Year-month fixed effects are included	Yes	Yes	Yes
Day of week and hours dummies are included	Yes	Yes	Yes
Seller controls are included	Yes	Yes	Yes
Housing controls	Yes	Yes	Yes
Obs	7176	2881	5898
R2	0.923	0.938	0.919

Notes: This tables uses data on housing units on the Parisian real estate markets between 2013 and 2019. There are three samples based on the 2013-2015 data, the 2016-2019 data (Liberty offer only) and the 2013-2019 data (Liberty offer only). The dependent variable is the estimated value of the housing unit according to the real estate agent. Standard errors clustered at the district level are presented in parenthesis. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

Table 9: Main results : Interacting dummy variables

	The dependent variable is the (log) estimated value	
	(1) Serenite (2013-2015)	(2) Three evaluations (2016-2019)
Coordination variable		
=1 if serenite offer	-0.044*** (0.005)	-0.029*** (0.009)
=1 if three agents visit the flat		0.027*** (0.008)
=1 if agents visit within a close period	-0.024** (0.010)	
Serenite × close moment	-0.021 (0.015)	
Housing characteristics		
size (square meters)	0.009*** (0.000)	0.010*** (0.000)
small housing unit: size ≤ 50sq.m	-1.162*** (0.034)	-1.128*** (0.039)
size × small housing unit	0.024*** (0.001)	0.023*** (0.001)
Agent characteristics		
experience	0.002 (0.003)	-0.009 (0.007)
Seller characteristics		
=1 if seller declares a minimum selling price	0.005 (0.005)	0.005 (0.010)
=1 if seller declares an ideal selling price	0.005 (0.005)	0.018* (0.011)
selling process already started	-0.001 (0.006)	-0.002 (0.009)
Real estate agency fixed effects are included	Yes	Yes
Zipcode fixed effects are included	Yes	Yes
Year-month fixed effects are included	Yes	Yes
Day of week and hours dummies are included	Yes	Yes
Seller controls are included	Yes	Yes
Housing controls	Yes	Yes
Obs	10619	5529
R2	0.925	0.933

Notes: This tables uses data on housing units on the Parisian real estate markets between 2013 and 2019. There are two samples based on the 2013-2019 data (only two evaluations per housing units) and the 2016-2019 data. The dependent variable is the estimated value of the housing unit according to the real estate agent. Standard errors clustered at the housing unit level are presented in parenthesis. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

Table 10: Main results : flats for which the buying price is known

	The dependent variable is the (log) estimated value		
	(1) Serenite (2013-2015)	(2) Three evaluations (2016-2019)	(3) Close moment (2013-2019)
Coordination variable			
=1 if serenite offer	-0.063*** (0.009)		
=1 if three agents visit the flat		0.030 (0.023)	
=1 if agents visit within a close period			-0.016 (0.018)
Housing characteristics			
size (square meters)	0.011*** (0.000)	0.014*** (0.001)	0.011*** (0.001)
small housing unit: size ≤ 50sq.m	-1.113*** (0.047)	-0.833*** (0.112)	-1.079*** (0.047)
size × small housing unit	0.023*** (0.001)	0.017*** (0.002)	0.023*** (0.001)
Agent characteristics			
experience	0.007 (0.007)	-0.016 (0.026)	0.006 (0.008)
Seller characteristics			
=1 if seller declares a minimum selling price	0.011 (0.009)	0.012 (0.049)	0.010 (0.010)
=1 if seller declares an ideal selling price	0.012 (0.009)	0.029 (0.046)	0.017 (0.011)
Buying price (log)	0.003 (0.003)	-0.006 (0.007)	0.005* (0.003)
selling process already started	0.003 (0.011)	0.033 (0.028)	0.018 (0.013)
Real estate agency fixed effects are included	Yes	Yes	Yes
Zipcode fixed effects are included	Yes	Yes	Yes
Year-month fixed effects are included	Yes	Yes	Yes
Day of week and hours dummies are included	Yes	Yes	Yes
Seller controls are included	Yes	Yes	Yes
Housing controls	Yes	Yes	Yes
Obs	2988	592	2382
R2	0.950	0.977	0.952

Notes: This tables uses data on housing units on the Parisian real estate markets between 2013 and 2019. There are three samples based on the 2013-2015 data, the 2016-2019 data (Liberty offer only) and the 2013-2019 data (Liberty offer only). The dependent variable is the estimated value of the housing unit according to the real estate agent. Here, we replicate our main results using an extra variable: the price paid by the seller when she initially bought the flat. Alternatively (and equivalently), we could use only the residuals from a preliminary regression where we would predict this buying price on explanatory variables. Standard errors clustered at the district level are presented in parenthesis. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

Table 11: Main results : impact of repeated interactions between agents

	The dependent variable is the (log) estimated value	
	(1) Serenite (2013-2015)	(2) Close moment (2013-2019)
Coordination variable		
=1 if serenite offer	-0.056*** (0.006)	
=1 if agents visit within a close period		-0.030*** (0.011)
No. collaborations between agents	-0.001*** (0.000)	-0.001*** (0.000)
Housing characteristics		
size (square meters)	0.009*** (0.001)	0.009*** (0.001)
small housing unit: size $\leq$ 50sq.m	-1.177*** (0.040)	-1.186*** (0.047)
size $\times$ small housing unit	0.024*** (0.001)	0.024*** (0.001)
Agent characteristics		
experience	0.002 (0.005)	0.001 (0.005)
Seller characteristics		
=1 if seller declares a minimum selling price	0.005 (0.006)	0.007 (0.007)
=1 if seller declares an ideal selling price	0.002 (0.006)	0.003 (0.007)
Buying price (log)		
selling process already started	-0.004 (0.008)	-0.002 (0.009)
Real estate agency fixed effects are included	Yes	Yes
Zipcode fixed effects are included	Yes	Yes
Year-month fixed effects are included	Yes	Yes
Day of week and hours dummies are included	Yes	Yes
Seller controls are included	Yes	Yes
Housing controls	Yes	Yes
Obs	7176	5898
R2	0.923	0.919

Notes: This tables uses data on housing units on the Parisian real estate markets between 2013 and 2019. There are two samples based on the 2013-2015 data and the 2013-2019 data (Liberty offer only). The dependent variable is the estimated value of the housing unit according to the real estate agent. Here, we replicate our main results adding the number of (observed) interactions between the two agents visiting the flat. Standard errors clustered at the district level are presented in parenthesis. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

Table 12: Pandering - taking into account minimum price

	The dependent variable is a dummy indicating that the agent panders		
	(1) Serenite (2013-2015)	(2) Three evaluations (2016-2019)	(3) Close moment (2013-2019)
Coordination variable			
=1 if serenite offer	-0.062*** (0.012)		
=1 if three agents visit the flat		-0.101 (0.084)	
=1 if agents visit within a close period			-0.010 (0.030)
Housing characteristics			
size (square meters)	0.001 (0.000)	0.001 (0.004)	0.000 (0.001)
small housing unit: size $\leq$ 50sq.m	0.132** (0.055)	0.093 (0.280)	0.116* (0.066)
size $\times$ small housing unit	-0.003** (0.001)	-0.001 (0.006)	-0.002 (0.001)
Agent characteristics			
experience	-0.001 (0.013)	0.008 (0.099)	-0.008 (0.015)
Seller characteristics			
=1 if seller declares a minimum selling price	0.080*** (0.013)	0.012 (0.058)	0.091*** (0.015)
selling process already started	-0.005 (0.016)	-0.011 (0.079)	-0.005 (0.020)
Real estate agency fixed effects are included	Yes	Yes	Yes
Zipcode fixed effects are included	Yes	Yes	Yes
Year-month fixed effects are included	Yes	Yes	Yes
Day of week and hours dummies are included	Yes	Yes	Yes
Seller controls are included	Yes	Yes	Yes
Housing controls	Yes	Yes	Yes
Obs	4392	481	3394
R2	0.139	0.687	0.185

Notes: This tables uses data on housing units on the Parisian real estate markets between 2013 and 2019. There are three samples based on the 2013-2015 data, the 2016-2019 data (Liberty offer only) and the 2013-2019 data (Liberty offer only). The dependent variable is whether the agent panders to the customer. Here, we consider cases where the agent confirms the ideal price of the customer and those where the agent confirms the minimum price of the customer. Standard errors clustered at the housing unit level are presented in parenthesis. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

Table 13: Pandering and estimation of housing units' value- taking into account minimum price

	The dependent variable is the (log) estimated value		
	(1) Serenite (2013-2015)	(2) Three evaluations (2016-2019)	(3) Close moment (2013-2019)
Coordination variable			
=1 if serenite offer	-0.055*** (0.006)		
=1 if three agents visit the flat		0.027*** (0.009)	
=1 if agents visit within a close period			-0.031*** (0.011)
= 1 if agent panders	0.018*** (0.007)	0.009 (0.024)	0.019** (0.008)
Housing characteristics			
size (square meters)	0.009*** (0.001)	0.010*** (0.000)	0.009*** (0.001)
small housing unit: size $\leq$ 50sq.m	-1.179*** (0.040)	-1.150*** (0.049)	-1.190*** (0.047)
size $\times$ small housing unit	0.024*** (0.001)	0.024*** (0.001)	0.024*** (0.001)
Agent characteristics			
experience	-0.001 (0.005)	-0.011 (0.010)	-0.002 (0.005)
Seller characteristics			
=1 if seller declares a minimum selling price	0.004 (0.006)	0.016 (0.015)	0.005 (0.007)
=1 if seller declares an ideal selling price	0.000 (0.006)	0.000 (0.017)	0.001 (0.007)
selling process already started	-0.004 (0.008)	0.007 (0.012)	-0.002 (0.009)
Real estate agency fixed effects are included	Yes	Yes	Yes
Zipcode fixed effects are included	Yes	Yes	Yes
Year-month fixed effects are included	Yes	Yes	Yes
Day of week and hours dummies are included	Yes	Yes	Yes
Seller controls are included	Yes	Yes	Yes
Housing controls	Yes	Yes	Yes
Obs	7176	2881	5898
R2	0.923	0.938	0.919

Notes: This tables uses data on housing units on the Parisian real estate markets between 2013 and 2019. There are three samples based on the 2013-2015 data, the 2016-2019 data (Liberty offer only) and the 2013-2019 data (Liberty offer only). The dependent variable is the log estimated value. We include a new explanatory variable capturing whether agents pander to the client. Here, we consider cases where the agent confirms the ideal price of the customer and those where the agent confirms the minimum price of the customer. Standard errors clustered at the housing unit level are presented in parenthesis. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

Table 14: Time to sell - survival analysis

	Analysis of the TOM		
sample:	(1) OLS Serenite (2013-2015)	(2) Weibull Serenite (2013-2015)	(3) Cox model Serenite (2013-2015)
Coordination variable			
=1 if serenite offer	0.110** (0.041)	0.243*** (0.086)	0.174** (0.085)
All mandates are exclusive	-0.042 (0.101)	1.085*** (0.103)	0.994*** (0.102)
Housing characteristics			
size (square meters)	-0.003 (0.002)	-0.005 (0.004)	-0.006 (0.004)
small housing unit: size $\leq$ 50sq.m	-1.051*** (0.275)	0.714* (0.389)	0.737* (0.386)
size $\times$ small housing unit	0.012** (0.005)	-0.006 (0.008)	-0.007 (0.008)
Seller characteristics			
=1 if seller declares a minimum selling price	0.033 (0.074)	-0.153* (0.087)	-0.124 (0.086)
=1 if seller declares an ideal selling price	-0.021 (0.094)	-0.063 (0.085)	-0.055 (0.084)
selling process already started	0.025 (0.071)	-0.047 (0.099)	-0.032 (0.097)
Zipcode controls	Yes	Yes	Yes
Year controls	No	Yes	Yes
Year-months controls	Yes	No	No
Seller controls are included	Yes	Yes	Yes
Housing controls	Yes	Yes	Yes
Obs	869	1545	1545

Notes: This tables uses data on housing units on the Parisian real estate markets between 2013 and 2019. There are three samples based on the 2013-2015 data, the 2016-2019 data (Liberty offer only) and the 2013-2019 data (Liberty offer only). In all cases, the sample is limited to housing units where we observe a listing price. The estimated models are survival-time models that assume exponential (1) and Weibull (2) distributions as well as the Cox proportional hazard models (3). Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.001$. We report the coefficients of the model. Lecture: a positive sign indicates that the hazard rate increases and therefore that the duration decreases.

Table 15: Time to sell - sample limited to exclusive mandates

	Analysis of the TOM				
	(1)	(2)	(3)	(4)	(5)
	OLS	Cox model	OLS	Weibull	Cox model
sample:	Three evaluations (2016-2019)	Three evaluations (2016-2019)	Close moment (2013-2019)	Close moment (2013-2019)	Close moment (2013-2019)
Coordination variable					
=1 if three agents visit the flat	-0.161 (0.111)	0.232 (0.181)			
=1 if agents visit within a close period			0.131 (0.285)	-0.031 (0.219)	-0.083 (0.218)
Housing characteristics					
size (square meters)	0.014** (0.006)	-0.000 (0.007)	-0.002 (0.007)	-0.004 (0.006)	-0.004 (0.006)
small housing unit: size $\leq$ 50sq.m	0.613 (0.423)	-0.113 (0.734)	-0.650 (0.507)	0.423 (0.622)	0.456 (0.614)
size $\times$ small housing unit	0.001 (0.010)	-0.001 (0.015)	0.005 (0.012)	0.000 (0.013)	-0.002 (0.013)
Seller characteristics					
=1 if seller declares a minimum selling price	0.047 (0.220)	-0.243 (0.303)	0.097 (0.104)	-0.229 (0.144)	-0.145 (0.143)
=1 if seller declares an ideal selling price	-0.257 (0.251)	0.232 (0.308)	-0.022 (0.119)	0.035 (0.151)	-0.001 (0.150)
selling process already started	-0.248 (0.174)	0.344 (0.256)	-0.181* (0.088)	0.190 (0.165)	0.152 (0.163)
Zipcode controls	Yes	Yes	Yes	Yes	Yes
Year controls	No	Yes	No	Yes	Yes
Year-months controls	Yes	No	Yes	No	No
Seller controls are included	Yes	Yes	Yes	Yes	Yes
Housing controls	Yes	Yes	Yes	Yes	Yes
Obs	263	332	399	594	594

Notes: This tables uses data on housing units on the Parisian real estate markets between 2013 and 2019. We report three specifications in two different samples (2016-2019 and 2013-2019). In all cases, the sample is limited to housing units where we observe a listing price. The estimated models are (1) OLS analysis of the time on market and survival-time models that assume Weibull distributions (2) as well as the Cox proportional hazard models (3). Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$. We report the coefficients of the model.

Lecture: in the OLS model, a positive sign indicates a longer time on the market whereas in the survival-time models, a positive sign indicates that the hazard rate increases and therefore that the duration decreases.
Remark: we did not report the Weibull model in the "three evaluation" case as it failed to converge.

7 Appendix: pandering and convenience rounding

In the main text, we show that real-estate agent sometimes estimate the value of housing units at exactly the same price that sellers indicated as their "ideal selling price." We also argue that this strategy does not correspond to a mere convenience rounding strategy. This affirmation relies on the following empirical methodology. First, we created the ratio between the value estimated by real-estate agents and the ideal prices informed by sellers. We kept only the value of the ratio that lie between 0.6 and 1.2. Second, we divided the previous interval into 120 bins of width 0.05 and counted the number of observations per bin. Third, we estimated a model where the dependent variable was the log number of observations per bin and the explanatory variables were a four-order polynomial function of the central value of the bin. However, when estimating the previous model, we exclude the bins in the interval $[0.958 - 1.015]$.

The previous procedure allows us to impute the number of observations that we would have observed in the absence of pandering on clients' wish and of convenience rounding. In order to do so, we compare the actual number of observations to the (exponential of

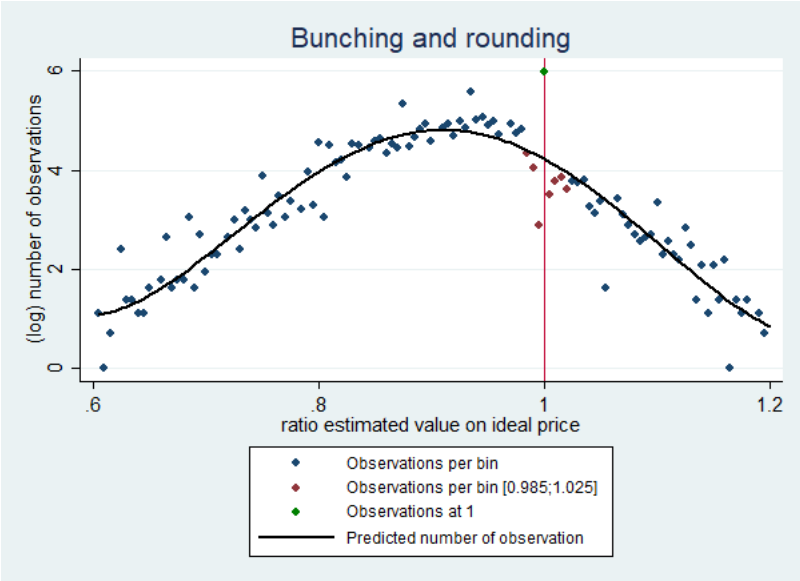


Figure 3: Number of observations per values of the ratio between the estimated value (by real estate agents) and the ideal price (logarithmic scale on the y-axis on the right).

the) predicted value given by our regression. Figure 3 depicts this procedure. The points correspond to the (log of the) observed number of observations per bin and the black curve represents the predicted number of observation according to our regression. As expected, the actual number of observations at the value 1 of the ratio (the green point) is well above the black curve, while observations are missing around 1 (the red points are located below the curve). Yet, interestingly, when we consider the entire interval $[0.958 - 1.015]$, the number of extra observations at 1 more than compensate the number of missing observations near 1. More specifically, we observe 399 observations at the value 1 of the ratio while our regression predicts that we should observe only 68 observations. We therefore have 331 extra observations. However, in the bins near 1, we observe on average 25 fewer observations than the number predicted by the regression. Taking this fact into account, the net number of extra observations is 204. Notice that, even taking into account these missing observations, we observe about 4 times more observations in 1. We therefore conclude that pandering on client wish is not limited to convenience rounding. [21]

[21] We make sure that our findings are robust to small modifications of our methodology, for instance taking larger intervals for computing extra and missing observations.

8 Theoretical appendix

In order to provide a simple and formal example to support economic intuition, we simplify the subsequent sale process to the extreme by considering that the good will actually be sold at the initial listing price p, but that the sale time is an increasing function of the difference between p and a reference price p_0. The seller is thus maximizing $pe^{-\delta T(p-p_0)}$ and, using a first order approximation, one can rewrite the expected utility (up to an additive constant) as a quadratic function $U = -(p - p^*)^2$. The price p^* is the optimal listing price for the client. The broker earns a percentage of the sale price and wants to sell more quickly, i.e. he has a lower discount rate $\delta' < \delta$. His expected utility can be rewritten in the same manner, up to a multiplicative constant, as $V = a-(p-(p^*-b))^2$ where $p^* - b$ is his optimal listing price. We recognize here the classical utility function in the explicit example worked out by Crawford and Sobel (1982) - except that in our case, this is not pure "cheap talk" since the client chooses freely the listing price only if he takes the outside option.

We also assume that the reference price of the house can take only two values, which results in two possible values of optimal listing prices for the client, noted respectively p_L and p_H. The client has an intial belief, described by the probability λ that his house has a high value, i.e. $p^* = p_H$. Broker observes the true value p^* and suggests a listing p^s equal to p_L or p_H according to a mixed strategy. Clients' beliefs λ are distributed uniformly on $[0, 1]$ and are Bayesian updated when they receive the proposal p^s from the broker. Clients either accept a broker's proposal, or sell on their own at a chosen price $p \in \{p_L, p_H\}$. [22] In that latter case, they incur an additional cost c reflecting the fact that they are less efficient than a professional broker in managing the sales process. We consider also a similar model with two brokers, in which clients can choose one of the two brokers or sell on his own.

[22] An enrichmnent of this model consists in allowing the customer to choose the optimal selling price in the interval $[p_L, p_H]$ according to his own belief. Such a model results in qualitatively identical results to those presented here.

The timing is as follows (the two-broker model is similar except that the client receives two proposals at $t = 0$ and then chooses in step $1a$ only one of the two brokers):

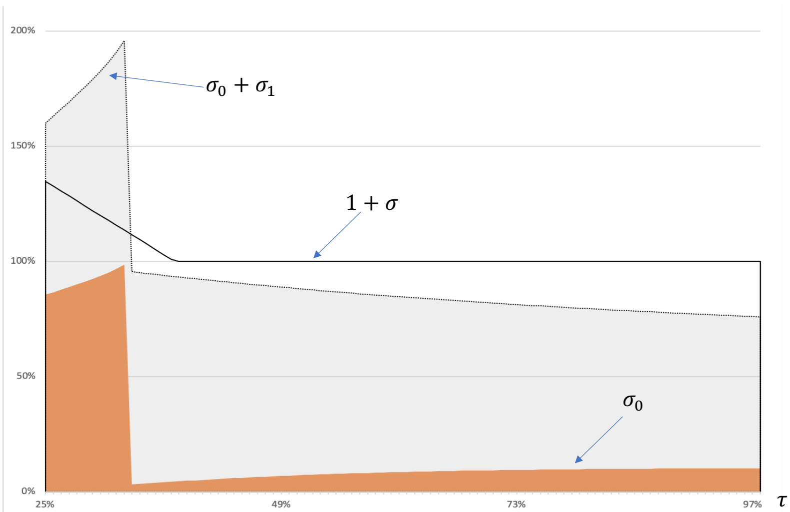
- $t = 0$: the broker observes $p^* \in \{p_L, p_H\}$ and sends a message p^s to the client. This message can take two values p_L or p_H. This is both what the agent claims to have observed, and what he therefore proposes as a listing price.
- $t = 1$: the client either (a) accepts p^s as a listing price and delegates the sale process to the broker, or (b) decides to sell his house on his own by choosing the other possible selling price p^c in $\{p_L, p_H\}$.
- $t > 1$: the house is sold and, depending on client's choice at $t = 1$:
  (a) client gets $U = -(p^s - p^*)^2$ and broker gets $V = a - (p^s - (p^* - b))^2$
  (b) broker gets nothing and client gets $U = -c - (p^c - p^*)^2$ where c is the additional cost having to sell by yourself.

As explain in the core text, we assume that the conflict of interest is strong enough so that the broker always prefers to sell at the low price. We also assume that the distribution of beliefs λ is uniform on $[0, 1]$ whereas the true share of high quality house on the market is denoted by λ^*. Besides, in the two-broker model, we limit ourselves here to symmetrical equilibria, since the client does not know the specificities of each agent (from his point of view, the two agents pursue a single and same strategy).

Without loss of generality, we set $p_L = 0$ and $p_H = 1$. The first assumption mentioned at the beginning of the previous paragraph is then equivalent to $b > 1/2$. We also assume $c < 1$ to prevent clients from being fully captive. We denote by τ the percentage of additional profit for real estate agents when selling a high quality house at a low price, and by τ' the percentage of profit lost when selling a low quality house at a high price. They are given by $1 + \tau = \frac{a-(1-b)^2}{a-b^2}$ and $1 - \tau' = \frac{a-(1+b)^2}{a-b^2}$. We assume $\tau' < 1$ and rule out the specific case where $(1 + \tau)(1 - \tau') = 1$. Lastly, we normalize broker's profit to one when he is selling at the true value, which is equivalent to say that broker's profit is respectively 1, $1-\tau'$ and $1+\tau$ when respectively selling at the true value, at a higher or lower value.

We characterize in the next sections the different equilibria with one and two brokers. Brokers' strategy can be described by two probabilities $\{\sigma_0, \sigma_1\}$ to reveal the real price when this price is respectively equal to 0 or 1. As explained in the core text, two equilibria can exist with one broker : the always low (AL) strategy $\{1, 0\}$ when clients are captive enough (high c) and the partial revelation (DB) strategy $\{1, \sigma_1\}$ in which the broker partially biases prices downward. With a second broker, another equilibrium may exist, in which brokers partially bias price both downward and upward (DU strategy with σ_0 and $\sigma_1 \in]0, 1[$). Numerical simulations are necessary to find out the equilibrium. The following graph describes it for a given set of data, with the additional profit τ when biasing downward represented on the x-axis. We see that for small value of τ, two brokers provide more information than a single broker, but this situation is reversed for higher value of τ. The two brokers only partially reveal the real price both when prices are high and low (DU strategy), whereas a single broker would always reveal a low price (AL or DB strategy).

Figure 4: Information revelation at the equilibrium for different value of τ



Notes: One-broker equilibria are characterized by $\{1, \sigma\}$ *where* σ *is the probability to reveal a high price. Two-broker equilibria are characterized by* $\{\sigma_0, \sigma_1\}$ *where* σ_0 *and* σ_1 *are the probability to reveal the real price when it is respectively low or high. The other parameters are* $c = 0.45$, $\tau' = 20\%$ *and* $\lambda^* = 1/2$.

8.1 One-broker model

If a client with belief λ accepts to sell with a broker at price $p = 1$ (resp. $p = 0$), his expected utility is $U = -(1-\lambda)$ (resp. $-\lambda$ when $p = 0$). If he decides to sell on his own, he chooses the other possible listing price and incurs an additional cost c. Thus, the client chooses the outside option when the high price is proposed iff $\lambda < (1-c)/2$ (resp. iff $\lambda > (1+c)/2$ when a low price is proposed). Broker's strategy is defined by the probabilites $\{\sigma_0, \sigma_1\}$ to tell the truth and propose $p^s = p^*$ when observing either 0 or 1. The client updates his belief accordingly using Bayesian rule, i.e. it becomes λ_1 (resp. λ_0) when receiving $p^s = 1$ (resp. 0) with

$$\lambda_1 = \frac{\lambda\sigma_1}{\lambda\sigma_1 + (1-\lambda)(1-\sigma_0)} \quad \text{and} \quad \lambda_0 = \frac{\lambda(1-\sigma_1)}{\lambda(1-\sigma_1) + (1-\lambda)\sigma_0}.$$

The seller prefers his outside option rather than accepting broker's proposal $p^s = 1$ (resp. $p^s = 0$) when $\lambda < \alpha_1$ (resp. $\lambda > \alpha_0$) with

$$\alpha_1 = \frac{(1-c)(1-\sigma_0)}{(1+c)\sigma_1 + (1-c)(1-\sigma_0)} \text{ and } \alpha_0 = \frac{(1+c)\sigma_0}{(1-c)(1-\sigma_1) + (1+c)\sigma_0}.$$

Regarding pure strategy, it is straightforward that the "always telling the truth" strategy $\{1, 1\}$ has a profitable deviation, that is sending $p^s = 0$ when p^* is equal to 1, and that the "always lying" strategy $\{0, 0\}$ is not a possible equilibria because all clients would go away. The "always proposing a high price" strategy $\{0, 1\}$ is not a possible equilibria either because the broker can deviate by sending $p^s = 0$. [23] The "always proposing a low price" $\{1, 0\}$ is an equilibrium since there are no profitable deviations. [24] In this later case,

[23] The client cannot not update his belief when there is an out-of-equilibrium message (because both deviations are profitable), so in both case the broker gets the same share of clients equal to $(1+c)/2$ but a higher per-client's profit when deviating.

[24] It must be noted that if $\tau' > 1$, then the second deviation ($p^s = 1$ when $p^* = 0$) is never profitable. The client can then by forward induction guess that $p^* = 1$ and accept broker's proposal. In that case, broker's profit is equal to 1, and the deviation gives less profit iff $(1+\tau)(1+c) > 2$. This possibility $\tau' > 1$ has been ruled out. Otherwise, proposition 1 would still be true, except that the "AL" equilibrium does not exist anymore when $(1+\tau)(1+c) < 2$.

we have $\alpha_0 = (1+c)/2$. It yields profit $\Pi_0 = ((1-\lambda^*) + \lambda^*(1+\tau))\alpha_0 = (1+\lambda^*\tau)(1+c)/2$. The average expert price is $\bar{p}^s = 0$, the average transaction price is $\bar{p} = 1-\alpha_0 = (1-c)/2$, and the average transaction price intermediated by a broker is $\bar{p}^i = 0$.

Let's now consider mixed strategies. For a given observation that can induces two different proposals, expected profit must be the same. Thus, sending a mixed signal when observing a high price (resp. a low price) requires $\alpha_0(1+\tau) = 1-\alpha_1$ (resp. $\alpha_0 = (1-\alpha_1)(1-\tau')$). By assumption, only one of those two relations can be true, so that there are four possible mixed strategies. The strategies $\{0, \sigma_1\}$ (resp. $\{\sigma_0, 0\}$) is not a possible equilibria since sending $p^s = 0$ (resp. $p^s = 1$) won't attract any customer. The strategy $\{\sigma_0, 1\}$ is not an equilibrium either since it implies $\alpha_0 = 1$, and the previous relation $\alpha_0 = (1-\alpha_1)(1-\tau')$ can not be satisfied. It remains the strategy $\{1, \sigma_1\}$ where σ_1 must satisfy the previous relation with $\alpha_1 = 0$, that is

$$\underbrace{\frac{1+c}{(1-c)(1-\sigma_1)+(1+c)}}_{=\alpha_0} \times (1+\tau) = 1 \tag{2}$$

or, equivalently, $\sigma_1 = 1 - \frac{1+c}{1-c}\tau$. Such a strategy exists iff $\sigma_1 > 0$, or equivalently $(1+\tau)(1+c) < 2$. It yields profit

$$\Pi_m = ((1-\lambda^* + \lambda^*(1-\sigma_1)(1+\tau))\alpha_0 + \lambda^*\sigma_1 = (1+\lambda^*\tau)\frac{1}{1+\tau} > \Pi_0$$

The average expert price is $\bar{p}^s = \lambda^*\sigma_1$, the average transaction price is $\bar{p} = (1-\alpha_0)(1-\lambda^* + \lambda^*(1-\sigma_1)) + \lambda^*\sigma_1 = 1-\alpha_0+\lambda^*\sigma_1$ and the average transaction price intermediated by a broker is

$$\bar{p}^i = \frac{\lambda^*\sigma_1}{\lambda^*\sigma_1 + (\lambda^*(1-\sigma_1)+(1-\lambda^*))\alpha_0} = \frac{\lambda^*\sigma_1}{\lambda^*\sigma_1 + (1-\lambda^*\sigma_1)\alpha_0}$$

We thus get the following result:

Proposition 1. *In the one-broker case, when $(1+\tau)(1+c) > 2$, the only equilibrium is the "always low price" pure strategy. Otherwise, there exists two possible equilibria,* *the "always low price" strategy (AL), and a mixed strategy with a downward bias (DB), according to which the agent tells the truth when observing a low price and lies with some probability when observing a high price, equal to* $1 - \sigma_1 = (1+c)\tau/(1-c)$.

8.2 Two-brokers model

We now assume that there are two experts $i = 1, 2$ that observe the price p^* and send proposals p_1 and p_2. We consider symmetric mixed strategies for the agents, denoted as in the previous section by $\{\sigma_0, \sigma_1\}$. Clients update their beliefs accordingly. When receiving twice the same message $p^s = 0$ (resp. $p^s = 1$), belief becomes λ_0 (resp. λ_1) where

$$\lambda_0 = \frac{\lambda(1-\sigma_1)^2}{\lambda(1-\sigma_1)^2 + (1-\lambda)\sigma_0^2} \text{ and } \lambda_1 = \frac{\lambda\sigma_1^2}{\lambda\sigma_1^2 + (1-\lambda)(1-\sigma_0)^2}$$

and client accepts brokers' proposal iff $\lambda_0 < (1+c)/2$ (resp. $\lambda_1 > (1-c)/2$) which can be rewritten as $\lambda < \alpha_0$ (resp. $\lambda > \alpha_1$) with

$$\alpha_0 = \frac{\sigma_0^2(1+c)}{(1-c)(1-\sigma_1)^2 + \sigma_0^2(1+c)} \text{ and } \alpha_1 = \frac{(1-\sigma_0)^2(1-c)}{(1+c)\sigma_1^2 + (1-\sigma_0)^2(1-c)}$$

When both brokers send the same message, and when the client decides to go through a broker, it is assumed that he will choose one of the two with equal probability. Lastly, when receiving two distinct messages 0 and 1, belief becomes

$$\lambda_{0,1} = \frac{\lambda\sigma_1(1-\sigma_1)}{\lambda\sigma_1(1-\sigma_1) + (1-\lambda)(1-\sigma_0)\sigma_0}$$

and client accepts broker's high price iff $\lambda_{0,1} > 1/2$, and chooses the other broker's low price otherwise. This last condition is equivalent to $\lambda > \alpha$ with

$$\alpha = \frac{(1-\sigma_0)\sigma_0}{(1-\sigma_0)\sigma_0 + (1-\sigma_1)\sigma_1}.$$

Let's first consider pure strategies. As in the previous section, the "always lying" strategy cannot be an equilibrium because all customers then prefer the outside opportunity (since $c < 1$). The "always proposing a high price" strategy is not an equilibrium because deviating is always profitable. [25] Similarly, the "always telling the truth" strategy cannot be an equilibrium since there is a profitable deviation when $p^* = 1$. [26] Lastly, let's consider the "always proposing a low price" strategy $\{1, 0\}$ ("AL"). It is an equilibrium if there are no profitable deviations. Since we assume $\tau' < 1$, both deviations are conceivable. Let's first assume that the client cannot not infer the true state when receiving two different price proposals. Then, when deviating from $p^* = 0$ (resp. $p^* = 1$), broker's benefit is $(1 - \tau')/2$ (resp. $1/2$) vs. $(1 + c)/4$ (resp. $(1 + c)(1 + \tau)/4$) when not deviating. If $(1 + c)(1 + \tau) \leq 2$, there is at least one profitable deviation (sending $p^s = 1$ when $p^* = 1$) and the "AL" strategy is not an equilibrium. [27] If $(1 + c)(1 + \tau) > 2$, the deviation when $p^* = 1$ is not profitable, the client can infer when receiving $p^s = 1$ that $p^* = 0$, which makes the other deviation non profitable either. It yields profit $\Pi_0 = ((1 - \lambda^*) + \lambda^*(1 + \tau))\alpha_0 = (1 + \lambda^*\tau)(1 + c)/4$. The average expert price and the average intermediated transaction price $\bar{p}^s = \bar{p}^i = 0$ whereas the average transaction price is $\bar{p} = 1 - \alpha_0 = (1 - c)/2$.

Let's now consider mixed equilibria. If a mixed message is sent when $p^* = 0$, i.e. $\sigma_0 \in]0, 1[$, broker's expected profit in that situation is

$$\alpha_0\sigma_0/2 + (1 - \sigma_0)\alpha = (1 - \tau')((1 - \alpha_1)(1 - \sigma_0)/2 + \sigma_0(1 - \alpha)) \tag{3}$$

[25] Indeed, with this strategy, we have $\alpha_1 = (1 - c)/2$ so that, when $p^* = 0$ (resp. $p^* = 1$), broker's benefit is $(1 + c)(1 - \tau')/4$ (resp. $(1 + c)/4$). When there is an out-of-equilibrium message, the client cannot not update his belief because both deviations are potentially profitable. Half of the clients choose the deviating broker, while the other half choose the other. Thus, when deviating with $p^* = 0$ (resp. $p^* = 1$), broker's benefit becomes $1/2$ (resp. $(1 + \tau)/2$), which is higher than what gives the initial strategy.

[26] We may assume instead that clients can infer the true state by forward induction, but it is then easy to see that there are no stable equilibrium in that case.

[27] Either the other deviating strategy is profitable, or the client can infer the true state and the first deviating strategy is even more profitable.

whereas if a mixed message is sent when $p^* = 1$, i.e. $\sigma_1 \in]0, 1[$, broker's expected profit is

$$(1 - \alpha_1)\sigma_1/2 + (1 - \sigma_1)(1 - \alpha) = (1 + \tau)(\alpha\sigma_1 + (1 - \sigma_1)\alpha_0/2) \tag{4}$$

If the only mixed message is when $p^* = 0$, then we have either σ_1 equal 0 or 1. The first case is impossible, otherwise no client would accept a broker's proposal at a high price. The second case is also not feasible, because it implies $\alpha_0 = \alpha = 1$, so that relation 3 can be rewritten as $1 - \sigma_0/2 = (1 - \tau')(1 - \alpha_1)(1 - \sigma_0)/2$ which is impossible. Thus, this "pure pandering" strategy is not an equilibria. If the only mixed message is when $p^* = 1$, then we have either σ_0 equal 0 or 1. Similarly, only the second case is possible. It implies $\alpha_1 = \alpha = 0$ so that relation 4 can be rewritten as $1 - \sigma_1/2 = (1 + \tau)(1 - \sigma_1)\alpha_0/2$. If this relation is satisfied, the strategy is an equilibrium if there is no profitable deviation when $p^* = 0$. This requires $\alpha_0/2 > (1 - \tau')$. Thus, this "partly lying downward" strategy is an equilibria iff there is a solution σ_1 to the equation 4 which can be rewritten as

$$\alpha_0 = \frac{1 + c}{1 + c + (1 - c)(1 - \sigma_1)^2} = \frac{1}{1 + \tau}(1 + \frac{1}{1 - \sigma_1}) \tag{5}$$

such that

$$\alpha_0/2 > (1 - \tau'). \tag{6}$$

Proposition 2. *There are three types of possible equilibria :*

- *the pure strategy AL when* $(1 + \tau)(1 + c) > 2$*;*
- *the "baising downard" strategy when relation 5 has a solution that satisfies 6;*
- *the "biaising upward and downward" strategy when relations 3 and 4 have a solution.*

The mixed strategies yield the profit (with $\alpha = 0$ and $\sigma_0 = 1$ in the former case)

$$\Pi_p = \lambda^*(1 + \tau)(\alpha\sigma_1 + (1 - \sigma_1)\alpha_0/2) + (1 - \lambda^*)(\alpha_0\sigma_0/2 + (1 - \sigma_0)\alpha)$$

and a numerical simulation is necessary to see whether those strategies exist and which one dominates. Such simulation is presented and discussed at the beginning of this section.

Table 16: Scambled data

	The dependent variable is the (log) estimated value		
	(1) Serenite (2013-2015)	(2) Three evaluations (2016-2019)	(3) Close moment (2013-2019)
Coordination variable			
=1 if serenite offer	-0.055*** (0.009)		
=1 if three agents visit the flat		0.022* (0.013)	
=1 if agents visit within a close period			-0.058*** (0.017)
Housing characteristics			
size (square meters)	0.005*** (0.000)	0.006*** (0.000)	0.005*** (0.000)
small housing unit: size $\leq$ 50sq.m	-0.659*** (0.037)	-0.651*** (0.060)	-0.663*** (0.042)
size $\times$ small housing unit	0.010*** (0.001)	0.010*** (0.001)	0.010*** (0.001)
Agent characteristics			
experience	-0.017*** (0.005)	0.055*** (0.014)	-0.007 (0.005)
Seller characteristics			
=1 if seller declares a minimum selling price	0.003 (0.007)	-0.007 (0.015)	0.007 (0.009)
=1 if seller declares an ideal selling price	0.001 (0.008)	0.017 (0.014)	-0.006 (0.009)
selling process already started	0.000 (0.009)	0.003 (0.015)	0.000 (0.009)
Real estate agency fixed effects are included	Yes	Yes	Yes
Zipcode fixed effects are included	Yes	Yes	Yes
Year-month fixed effects are included	Yes	Yes	Yes
Day of week and hours dummies are included	Yes	Yes	Yes
Seller controls are included	Yes	Yes	Yes
Housing controls	Yes	Yes	Yes
Obs	7176	2881	5898
R2	0.861	0.879	0.861

Table 17: Scambled data

	The dependent variable is					
	(1) listing price	(2) selling price	(3) listing price	(4) selling price	(5) listing price	(6) selling price
sample:	Serenite (2013-2015)	Serenite (2013-2015)	Three evaluations (2016-2019)	Three evaluations (2016-2019)	Close moment (2013-2019)	Close moment (2013-2019)
Coordination variable						
=1 if serenite offer	-0.028 (0.020)	-0.055 (0.036)				
=1 if three agents visit the flat			0.040 (0.028)	0.019 (0.057)		
=1 if agents visit within a close period					-0.146*** (0.045)	-0.380*** (0.102)
All mandates are exclusive	-0.033 (0.021)	-0.008 (0.051)	-0.010 (0.035)	-0.002 (0.111)	-0.035* (0.020)	-0.038 (0.037)
Housing characteristics						
size (square meters)	0.006*** (0.000)	0.010*** (0.000)	0.006*** (0.000)	0.009*** (0.001)	0.006*** (0.000)	0.010*** (0.001)
small housing unit: size $\leq$ 50sq.m	-0.622*** (0.075)	-0.730*** (0.134)	-0.856*** (0.086)	-0.951*** (0.171)	-0.656*** (0.103)	-0.768*** (0.244)
size $\times$ small housing unit	0.010*** (0.002)	0.013*** (0.003)	0.017*** (0.002)	0.017*** (0.004)	0.011*** (0.002)	0.016*** (0.005)
Seller characteristics						
=1 if seller declares a minimum selling price	0.007 (0.013)	-0.043 (0.030)	-0.015 (0.030)	-0.097 (0.076)	-0.012 (0.015)	-0.086* (0.042)
=1 if seller declares an ideal selling price	-0.013 (0.011)	0.003 (0.039)	0.013 (0.028)	0.010 (0.059)	-0.023 (0.017)	0.041 (0.058)
selling process already started	-0.007 (0.017)	-0.012 (0.033)	-0.002 (0.036)	-0.060 (0.096)	0.004 (0.024)	0.032 (0.050)
Zipcode fixed effects are included	Yes	Yes	Yes	Yes	Yes	Yes
Year-month fixed effects are included	Yes	Yes	Yes	Yes	Yes	Yes
Seller controls are included	Yes	Yes	Yes	Yes	Yes	Yes
Housing controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1618	896	826	437	1317	625
R2	0.858	0.802	0.880	0.838	0.859	0.808

Table 18: Scambled data

	Analysis of the TOM					
	(1) OLS	(2) Weibull	(3) Cox model	(4) OLS	(5) Weibull	(6) Cox model
sample:	Three evaluations (2016-2019)	Three evaluations (2016-2019)	Three evaluations (2016-2019)	Close moment (2013-2019)	Close moment (2013-2019)	Close moment (2013-2019)
main						
Coordination variable						
=1 if three agents visit the flat	-0.104 (0.151)	0.320** (0.151)	0.315** (0.150)			
=1 if agents visit within a close period				-0.224 (0.154)	-0.062 (0.169)	-0.078 (0.168)
All mandates are exclusive	-0.056 (0.204)	1.292*** (0.190)	1.195*** (0.187)	-0.201* (0.107)	1.142*** (0.103)	1.056*** (0.101)
Housing characteristics						
size (square meters)	0.003* (0.002)	0.004** (0.002)	0.004** (0.002)	0.001 (0.001)	-0.001 (0.001)	-0.002 (0.001)
small housing unit: size $\leq$ 50sq.m	0.076 (0.597)	0.189 (0.431)	0.207 (0.433)	0.216 (0.305)	-0.502 (0.320)	-0.428 (0.322)
size $\times$ small housing unit	-0.004 (0.017)	-0.009 (0.011)	-0.010 (0.011)	-0.002 (0.009)	0.012 (0.008)	0.011 (0.008)
Seller characteristics						
=1 if seller declares a minimum selling price	-0.124 (0.180)	-0.061 (0.173)	-0.054 (0.173)	0.099 (0.109)	0.005 (0.102)	0.019 (0.101)
=1 if seller declares an ideal selling price	0.042 (0.152)	0.220 (0.178)	0.193 (0.176)	-0.069 (0.094)	0.017 (0.104)	0.015 (0.103)
selling process already started	-0.062 (0.194)	0.007 (0.176)	0.032 (0.174)	-0.034 (0.099)	0.006 (0.110)	0.004 (0.109)
Zipcode controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	No	Yes	Yes	No	Yes	Yes
Year-months controls	Yes	No	No	Yes	No	No
Seller controls are included	Yes	Yes	Yes	Yes	Yes	Yes
Housing controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	319	471	471	580	1200	1200