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The Effects of Time Constraints on Broker Behavior in China's Resale Housing Market: Theory and Evidence

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This study examines the effects of time pressure on residential real estate broker behavior. Consistent with our intuition, we find that when under a binding time constraint, brokers do transact the property more quickly, but do not work as hard and ultimately recommend less optimal homes. Interestingly, brokers earn the same commission when operating in either a low or high time pressure environment. When the characteristics of the broker are considered, we find that experienced brokers are significantly more effective at matching buyers and sellers under time constrained conditions.

Keywords

China, Search Duration, Time Constraints, Residential Real Estate

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1. Introduction

Buying a home is one of, if not the, largest purchase that a person will ever make. Moreover, the goal of homeownership is often constrained by a major life event, such as relocating to take a new job, getting married, or having children. While social scientists generally recognize that time pressure impacts the tradeoff between decision speed and accuracy, no study has ever been conducted to understand the impact of time pressure on decision-making in a residential real estate setting. Are speed and accuracy necessary tradeoffs in residential real estate? Are some brokers more successful at matching buyers and sellers under time constrained conditions? Is a more efficient broker also a more effective broker? We are the first to answer these specific questions associated with buying residential real estate when operating under a time constraint – which is very often the case for homebuyers.

While transaction data reveal what a property ultimately sold for in the marketplace, it is completely silent on any measure of time constraint faced by the buyer of the property. Since the underlying home purchase process is not recorded until the final transaction stage, field data are not helpful in answering our research questions. Instead, we collect data on the search process by employing an experimental design. When working with transaction data, researchers seek to hold all else constant through the inclusion of an extensive list of explanatory variables and advanced econometric techniques. In a controlled experiment, ceteris paribus is achieved through a careful research design. Whereas transaction data require the assumption that the real world can be held constant through the inclusion of key independent variables, an experiment assumes that the results found in a controlled laboratory environment continue to hold in the real world. In this sense, traditional regression analysis and experimental design are two different data collection techniques that merely differ in terms of when they attempt to hold all extraneous influences constant. A regression analysis controls for outside influences on the back end, while an experimental design controls for outside influences on the front end.

Experimental design methodologies have been around for decades, but are more recently burgeoning in popularity (Northcraft and Neale, 1986; Yavas, Miceli, and Sirmans, 2001; Ong, et al., 2003; Yavas and Sirmans, 2005; Seiler et al., 2012; Ikromov and Yavas, 2012a, 2012b; and Seiler, 2014). As such, we incorporate the experimental approach of Yavas, Miceli, and Sirmans (2001) and Ikromov and Yavas (2012a, 2012b) to isolate the effect of time pressure on broker behavior when conducting a home search.

We make a contribution to the literature on several fronts. We are the first to examine the effect of time constraints on the residential home search process. We provide a theoretical model to support our hypothesized relations and then necessarily use an experimental design to collect data on the effort and

effectiveness of brokers to match buyers with their specified home characteristic stated preferences. By using actual brokers (as opposed to students which have been used in past studies), we find that when facing a time constraint, brokers comply by transacting the sale, but put forth less effort and recommend sub-optimal homes. Interestingly, despite doing less work and under-performing, brokers experience the same level of earnings as when operating in a low time pressure environment. When considering the characteristics of the broker, we find that experience is significant in explaining the differentially superior ability of a broker to match buyers and sellers.

2. Time Pressure Literature

Ben Zur and Breznitz (1981) examine the behavior of traders who are facing progressively more restrictive decision windows and find that when put under pressure, investors will choose less risky investments. Payne, Bettman and Johnson (1993) construct an effort/accuracy model which suggests that decision-makers will make a necessary tradeoff between speed and accuracy when facing a time constraint. That is, greater time pressure means less effort will be exerted, resulting in lower decision quality.

When playing the ultimatum game, Sutter, Kocher and Strauß (2003) find that increased time pressure results in a greater likelihood of offers being rejected. Interestingly, this effect dissipates with experience. It seems that as players gain experience working in a time pressured environment, they are more able to use cognitive short cuts, or heuristics, to guide them to better decision-making. Payne, Bettman and Johnson (1993) and Rubinstein (2007) suggest that this level of efficiency is easier to achieve when making instinctive or emotional decisions as opposed to decisions that require more cognitive power.

Ibanez, Czermak and Sutter (2009) specifically examine how search behavior is affected by time pressure. In the rounds of their experiment when the subjects were still inexperienced, time pressure significantly resulted in sub-optimal choices. However, as the subjects became more experienced in playing the game, the magnitude of the impact dissipated, thus reflecting a learning curve effect. In sum, more experience leads to quicker decision-making. Interestingly, accuracy rates remain relatively constant over time, which implies the absence of a speed-accuracy tradeoff.

To date, no study has examined the impact of a time constraint on the search process for buying residential real estate. Extant literature, such as the classical study by Yinger (1981) and well cited papers by Jud (1983), Jud and Frew (1986), Baryla and Zumpano (1995), Elder, Zumpano and Baryla (2000; 1999), Anglin (1997), and Zietz and Newsome (2001), examine the impact of brokers on the search process. However, no study to date has examined the impact of time pressure on a broker to efficiently and effectively perform his/her functions.

That the brokerage industry is characterized by both instinctive decisions and financial calculations presents an interesting empirical question. Will the emotional/instinctive nature of brokerage decision-making cause experienced brokers to perform better than non-experienced brokers when facing a time pressure, or will the financial calculation component of matching buyers and sellers at the right price cause brokers to perform sub-optimally when facing a time constraint? These are empirical questions that can be definitely answered through the careful construction of an experimental design, which we discuss in an upcoming section.

3. Broker Service in Resale Housing Market in China

Brokers in the resale housing market in China provide services for buyers and sellers primarily during the matching stages of the purchase process. Once a buyer and seller enter the bargaining stage, the role of the broker is mitigated to a more communicative function; brokers do not actively negotiate on behalf of their clients. As a result, the Chinese resale market is the ideal marketplace to study the impact of time pressure on the search process (as opposed to the negotiation process). As such, this study focuses on the searching and matching functions of brokers, not on their lesser important negotiating role.

The housing search process in China can be divided into three main phases: (1) the buyer specifies his/her housing preferences to several brokers; (2) by incorporating the preference set of the buyer, brokers then independently recommend homes to the buyer; and (3) when the search results for the buyer results in a match, the buyer bargains with the seller to negotiate a transaction. Only the broker who ultimately matches the buyer with the house that is purchased receives a commission.

China has yet to create a uniform and market-wide residential real estate database where all sellers list their homes for sale (like the Multiple Listing Service in the United States). Instead, information on available homes is sparse and fragmented. In addition, the appearance of "True and False Contracts"[1] is widespread in the resale housing market. The lack of quality data severely hampers research related to Chinese housing search issues. As such, this is another reason that we seek to understand the effect of time pressure on residential home searches by using an experimental design.

[1] A "True Contract" refers to one where the actual transaction price is accurately reported, whereas a "False Contract" describes one of two possibilities. One example of a false contract is when a higher price is reported to allow for the application of a larger mortgage from the lender. The second is a lower reported price designed to reduce real estate taxes owed.

4. Experimental Design

Within the experiment, four professional brokers compete for the business of the buyer by recommending homes to him/her that best match his/her stated preferences.[2] The brokers are actual practicing professionals in the local housing market, whereas the buyer is represented by a computer program.[3] A total of 20 homes are available for recommendation.

The buyer makes a comprehensive evaluation of each available home based on five attributes: age of the home, view, floor level, condition, and access to transportation. The utility function for the buyer to make his/her purchase decision is based on the following equation:

$$\pi_b = \sum_{i=1}^{5} b_i Q_i - P - P \times \alpha \tag{1}$$

where π_b is the utility function of the buyer, b_i is the evaluation coefficient of the buyer on the i^{th} housing attribute, Q_i is the level of the i^{th} housing attribute, P is the transaction price, and α is the commission percentage. Each attribute is measured on an equally spaced, 4-point scale labeled A, B, C and D, with corresponding values 4, 3, 2, and 1. Attribute levels associated with the 20 homes are listed in Table 1, and are again, reflective of the actual housing market. The parameter values for the utility function of the buyer are shown in Table 2.

To collect our data, we use a popular experimental market platform known as z-Tree (Fischbacher, 2007), a screenshot of which is shown in Figure 1. In each session, the four brokers compete by recommending a home from a list of 20 available houses for sale in the lower-left screen. To convey the recommendation to the buyer, the broker simply enters the housing number to be recommended and the proposed sale price in the middle of the right side of the screen, and then clicks the "Calculate" button. If the home recommended by the broker is an improvement over the previous recommendation (in terms of either a better match or a lower price), this new recommendation will be displayed in the upper-left “housing recommendations records” area and the

[2]This design reflects the characteristics of the resale housing market in China. A broker does not charge any fees before achieving a transaction, and will get an agent fee from the buyer when matched, with no fee from the seller. To expedite the search process, a buyer asks several brokers from different companies to simultaneously recommend houses that meet his/her specified preferences. In addition, 2012 market survey results from the Institute of Real Estate Studies at Tsinghua University show that, on average, 4.2 brokers are commissioned to provide services to buyers during the home search process.

[3] We have the computer play the role of the buyer for two reasons. First, the focus of this study is on broker behavior. Thus, we want to hold constant the behavior of the buyer. Secondly, since we are controlling for time in this study, a computer program further supports consistent and timely feedback to brokers in terms of accepting offers.

upper-right "buyer's most satisfactory housing records" area of the screen in real time. If any broker recommends a more satisfactory home to the buyer before the clock counts down to zero, the buyer will update the information about the currently most satisfactory home and its corresponding price. Otherwise, at the end of the countdown, the buyer will purchase the most satisfactory home, and the round will end.

Table 1 List of Available Homes and their Attributes

This table displays the parameters of the 20 homes listed for sale. Letters A~D (high to low) reflect the quality of each home characteristic attribute on a consistent 4-point scale.

Home Number	Age	View	Floor Level	Condition	Access to Transportation	Seller's Reservation Price (in thousands)
1	A	B	C	D	B	250
2	B	A	B	C	D	260
3	C	D	A	B	B	270
4	B	C	D	A	B	250
5	D	B	C	B	A	265
6	A	A	B	C	D	275
7	B	A	A	C	D	285
8	C	B	A	A	D	290
9	D	C	B	A	A	290
10	A	B	C	D	A	270
11	A	A	A	D	C	320
12	B	A	A	A	C	345
13	D	C	A	A	A	315
14	A	C	D	A	A	285
15	A	A	C	D	A	290
16	A	A	A	A	D	340
17	D	A	A	A	A	355
18	A	D	A	A	A	340
19	A	A	D	A	A	325
20	A	A	A	D	A	340

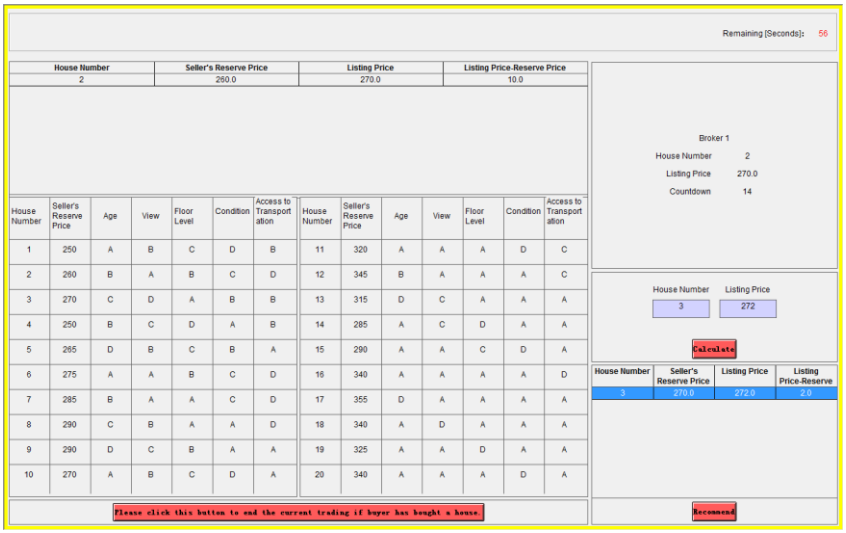
Table 2 Experimental Design Parameters

This table shows the parameters of the 10 formal trading sessions within the experiment. The sum of all five attribute values equals the reservation price of the buyer.

Attributes	Value of Parameters (Ten Thousand of Experimental Currency) in each Session									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Age	25	13	13	18	24	10	15	23	17	5
View	23	15	23	18	23	23	20	22	30	24
Floor Level	20	28	30	23	22	35	20	13	21	24
Condition	18	23	18	18	16	18	18	17	19	30
Access to Transportation	16	23	17	24	17	16	30	25	16	20

Figure 1 Screen Capture of the Graphical User Interface

This figure shows a screen capture of what the subject sees during the experiment.



To align our experimental marketplace with that of the actual market, we incentivize brokers by compensating them based on performance (Smith, Suchanek, and Williams, 1988). Specifically, compensation consists of a show-up fee of 150 China yuan (spendable local currency),[4] as well as commissions earned from the sale of a home. Experimental earnings include (1) the difference between the transaction price of a home and the reservation price of the seller, and (2) a commission in the amount of 2.5% of the transaction price of the home.

After the experiment, the broker exchanges the experimental market earnings for spendable China yuan. The exchange rate is 10,000 experimental currency units to 1 China yuan. The earning function of the broker is:

$$\pi_i = \begin{cases} P - C + P \times 2.5\% - N \times 100 & \text{if buyers accept the recommended house;} \\ -N \times 100 & \text{otherwise} \end{cases} \tag{2}$$

where π_s is the earnings of the broker, P is the transaction price, C is the reservation price of the seller, N is the number of recommended homes, 2.5% is the sales commission, and 100 experimental currency units is the single recommendation cost of the broker.

[4] We design the expected compensation to be consistent with the actual per hour salary that brokers earn in the actual marketplace.

To correctly quantify what constitutes a high versus low pressure constraint, we follow the methodology of Svenson and Benson (1993). Specifically, by using a holdout sample of brokers, we first measure the mean time required for decision-makers to complete the task without any time pressure as well as the standard deviation across all brokers. The low pressure decision time is equal to the average decision time minus one standard deviation. The high pressure decision time is equal to the average decision multiplied by three standard deviations. In conducting these tests, the standard decision time is 13.11 seconds and the standard deviation of decision time is 1.86 seconds. Hence, we define in our study the low time pressure decision time as 11.25 (13.11 – 1.86) seconds, while the high pressure decision time is 7.53 (13.11 – [3]*[1.86]) seconds.

5. Sample Participants

While past studies, such as Yavas, Miceli, and Sirmans (2001) and Ikromov and Yavas (2012a, 2012b), use students as a convenience sample, we argue that it is better to use actual market participants when possible because they are the ones whose behavior we wish to examine. For this reason, we recruited actual practicing professional brokers to participate in our study. Within one week after releasing the recruitment announcement, a total of 421 brokers enrolled, from which we randomly selected 128 brokers to participate in (only one session of) the experiment. Half the sample is used in pre-testing to determine the high versus low time pressure conditions, while the remaining 64 brokers participate in the experiment whose results are reported as the core findings of this study.

In comparing the demographics of our participating brokers to that of a market-wide survey carried out jointly by the Ministry of Housing and Urban-Rural Development and the China Institute of Real Estate Appraisers and Agents in 2010, we find that our sample is reasonably representative of the typical broker. Specifically, 25% (20%) of our broker participants (all brokers) have a Bachelor's degree or above, and 75% (69%) of our broker participants (all brokers) range from 20 to 29 in age. The complete descriptive statistics of the sample are given in Table 3.

Table 3 Broker Characteristic Descriptive Statistics

This table provides the basic descriptive statistics (sample size, minimum, maximum, mean and standard deviations) for the 64 professional broker participants. *Gender* is defined as 1=Male; 0=Female. *Education* is defined as 1=college degree; 0 otherwise. *Experience* is the number of years the broker has worked in the industry. *Age* is the age of the broker in years.

Variable	N	Minimum	Maximum	Mean	Standard Deviation
Gender	64	0	1	0.656	0.479
Education	64	0	1	0.250	0.436
Experience	64	1	8	3.594	2.091
Age	64	19	43	26.203	5.595

6. Experimental Procedures

The pre-experiment process begins when the subjects read the trading instructions on their own. These same instructions are then read aloud by the person who is conducting the experiment followed by the opportunity for the participants to ask questions. Next, the participants are shown exactly how to use the software through a group demonstration. Finally, the participants complete a comprehension test before starting the actual experiment. Once the experimenter is certain that everyone understands the instructions, the brokers participate in three practice periods. The three practice periods are intended to allow the participants to become familiar with the computer interface and learn how to recommend a home to the buyer. The three practice sessions are followed by 10 actual trading sessions where compensation is directly tied to performance.[5] In terms of the final sample size, we conduct a set of 10 trading sessions across 16 different groups with each containing 4 brokers. As such, we examine the behavior of 64 (16 x 4) professional brokers who match buyers with 160 (16 x 10) homes.

7. Experimental Results

7.1 The Effects of Time Pressure on Behavior of Brokers

The experimental results are automatically recorded by the z-Tree software program. In order to quantify the behavior of the brokers, we calculate an "effort index" and an "effectiveness index". The effort index is defined as the total number of recommendations made by the brokers; a greater number of recommendations means that greater effort is put forth. To evaluate the effectiveness of the recommendations of the brokers, we define both a matching index and a search duration index. The matching index is defined as the Euclidean distance, or the difference between the ideal home for the buyer and what the broker has recommended. A smaller Euclidean distance means that the broker has a better performance.

$$ED = \sqrt{\sum_{i=1}^{5} (Q_{io} - Q_{it})^2} \tag{3}$$

where *ED* is the Euclidean distance, Q_{io} is the level of the actual attributes of the i^{th} home and Q_{it} is the level of the ideal attributes of the i^{th} home as specified by the buyer.

The second measure of broker effectiveness is his/her ability to quickly match the buyer with a home. Search duration is defined as the time that elapses between the commencement of the trading period to the time of the transaction (or the end of the trading session, whichever comes first). A shorter search duration means that the broker has a better performance.

[5] All participants are compensated before leaving the experiment.

Table 4 Impact of Time Pressure on Broker Behavior

This table reports the statistics of the effort and effectiveness indexes in high and low time pressure sessions. Mann-Whitney U tests quantify the impact of time pressure on the service provided by the broker. Panel A reports the results for all sessions; Panel B reports the results for only the perfectly matched (i.e., ED=0) sessions; and Panel C reports the results for only imperfectly matched (i.e., ED>0) sessions.

Panel A: Sample Size of All Sessions =160						
Index type	**Measure**	**High time pressure sessions**		**Low time pressure sessions**		***Mann-Whitney U test*** **(p-value)**
		Mean	**Standard Deviation**	**Mean**	**Standard Deviation**	
Effort index	Number of recommendations	8.58	3.57	12.88	5.10	Yes (0.000)
Effectiveness index	Euclidean distance	1.33	1.42	0.73	1.26	Yes (0.002)
	Search duration (Seconds)	56.30	21.95	82.98	33.11	Yes (0.000)
Sample Size		80		80		
Panel B: Euclidean Distance =0; Sample Size of ED = 0 Sessions = 91						
Effort index	Number of recommendations	9.278	3.067	13.600	4.581	Yes (0.000)
Effectiveness index	Euclidean distance	0	0	0	0	
	Search duration (Seconds)	59.083	24.381	82.236	28.683	Yes (0.000)
Sample Size		36		55		
Panel C: Euclidean Distance >0; Sample Size of All ED>0 Sessions = 69						
Effort index	Number of recommendations	8.000	3.906	12.900	5.476	Yes (0.000)
Effectiveness index	Euclidean distance	2.426	1.024	2.489	1.260	No (0.971)
	Search duration (Seconds)	54.023	20.010	91.750	44.574	Yes (0.000)
Sample Size		44		25		

Panel A of Table 4 reports the results for the 160 home transactions segmented by high versus low time pressure trials. In terms of effort, the brokers exert significantly less effort when faced with a time constraint (8.58 vs. 12.88 recommendations). In terms of effectiveness, the Euclidean distance is significantly greater (1.33 vs. 0.73) when operating in high pressure sessions. That is, buyers are not matched with as appropriate a home when time is restricted. Finally, when examining the search duration, transactions do occur significantly sooner (56.30 vs. 82.98) in the high pressure constrained environment. In sum, it seems that brokers respect the time constraint by closing transactions within the time allowed, but in their haste, make fewer recommendations that result in homes that do not as closely match the preferences of buyers as they would if the brokers had more time to make better home recommendations.

To more deeply analyze the matching success under high versus low time pressure conditions, we split the sample of 160 home transactions into sessions where the ideal home is recommended by a broker (i.e., ED = 0) versus sessions where the "best" home is not recommended by a broker (i.e., ED > 0). Panel B considers the 91 sessions where the optimal home is matched with the buyer, whereas Panel C reports the results associated with the remaining 69 sessions where the optimal home is not matched with the buyer. Consistent with Panel A, the brokers make significantly fewer recommendations in the high pressure trials, but sell homes significantly more quickly. The impact of time pressure is further evident when examining the number of sessions in which ED = 0. Of the 91 ED = 0 sessions, 55 occur in the low time pressure condition (as opposed to 36 in the high pressure condition). Alternatively stated, for high pressure trials, over half (44/80) result in sub-optimal matches, whereas in low pressure trials, only 25 of the 80 sessions end in the sub-optimal matching of buyers with homes. In sum, the search for a home under a severe time constraint leads to fewer broker recommendations and a poorer outcome. However, that result is achieved faster (as required by the time constraint).

7.2 Broker Characteristics

To ensure that the individual characteristics of the broker are not driving the results, we next incorporate them into a multi-variate analysis by using two different model specifications. Specifically, Model 1 employs a logistic regression where the dependent variable is equal to 1 in sessions where a "perfect match (i.e., ED = 0)" has been found by the broker, 0 otherwise (i.e., ED > 0). Alternatively specified, Model 2 leaves ED as a continuous variable. Since in 91 of the 160 sessions ED = 0, we model the relationship by employing a censored Tobit regression.

Columns 1 and 2 of Table 5 report the results for all 160 trading sessions. Consistent with our previous findings, the coefficient on the time pressure variable confirms that high pressure searches result in significantly poorer search outcomes in terms of matching buyer preferences with recommended

homes. That no broker characteristic variable is significant adds support to our finding that it is truly the time pressure constraint that is driving our results. As an even further robustness check, Columns 3~6 re-estimate the models that segment the data by high and low pressure sessions. Again, the addition of confidence to our central hypothesis results in the finding that no broker characteristic variables are significant[7].

7.3 Determinants of Broker Commissions

We now shift our focus to understanding which broker characteristics are associated with earning higher commissions under high and low time pressure constraints. Alternatively explained, while four brokers compete to recommend marginally better homes to the buyer throughout each session, our focus now is on which broker ultimately makes the winning, or most optimal, recommendation.

7.3.1 Gender

Conclusions related to the effect of gender on the commission of a real estate broker are mixed. Abelson, Kacmar and Jackofsky (1990) find that woman perform better than men in the residential real estate marketplace. On the contrary, Crellin, Frew and Jud (1988), Sirmans and Swicegood (1997), and Jud and Winkler (1998) find that men have the gender advantage in the residential brokerage industry. Follain, Lutes and Meier (1996), Turnbull and Dombrow (2007) conclude that gender has no influence on broker income. Given the inconsistent and sometimes null results, we leave the sign of this variable as an open empirical question.

7.3.2 Education

Previous studies (Crellin, Frew and Jud, 1988; Glower and Hendershott, 1988; Abelson, Kacmar and Jackofsky, 1990) find a positive relation between the degree of education and broker compensation. Interestingly, Jud and Winkler (1998) conclude that the relation is positive for males and negative for females. Benjamin et al. (2007) have conducted a study based on data from a cross-sectional survey of 6,842 real estate licensees and find that schooling and experience decrease the work effort of brokers, but increase their work efficiency. As such, we hypothesize a positive relation between education and earnings, if any.

[7] In unreported results, we also estimate regressions where broker characteristics and the time pressure dummy variable are regressed against the dependent variables of search duration and number of broker recommendations. Again, only the time pressure variable is significant, further supporting our reported findings. These additional tables are available from the authors upon request.

Table 5 Determinants of Broker Effectiveness as Measured by Euclidean Distance

This table reports the determinants of broker effectiveness in terms of their ability to match buyers with their ideal home. In Models 1, 3, & 5, a logistic regression is used as the dependent variable, and equal to 1 when a perfect match occurs (i.e., ED = 0), 0 otherwise. In Models 2, 4, & 6, a censored Tobit regression is used because the dependent variable, ED, is a continuous variable that often contains a value of 0. *Male Dummy* is defined as 1=Male; 0=otherwise. College *Degree Dummy* is defined as 1=college degree; 0 otherwise. *Experience* is the number of years that the broker has worked in the industry. *Age* is the age of the broker in years. *High Pressure Dummy* is defined as 1=high pressure trials; 0=otherwise. ** indicates a significance level of 99% while * indicates significance at 95%. Standard errors are provided in parentheses.

	Full Sample		High Pressure		Low Pressure	
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Constant	0.700	0.500	-0.097	1.039	1.420	0.749
	(0.531)	(0.358)	(1.142)	(1.437)	(1.378)	(0.434)
Male Dummy	-0.240	0.276	-0.108	-0.221	-0.939	-0.260
	(0.232)	(0.544)	(0.503)	(0.629)	(0.639)	(0.171)
College Degree Dummy	-0.175	0.147	-.0.515	0.312	0.041	0.013
	(0.233)	(0.544)	(0.516)	(0.635)	(0.593)	(0.180)
Experience	0.003	-0.027	0.000	-0.023	0.116	0.036
	(0.049)	(0.116)	(0.112)	(0.141)	(0.121)	(0.037)
Age	-0.005	-0.007	0.006	-0.011	-0.017	-0.006
	(0.018)	(0.041)	(0.044)	(0.056)	(0.040)	(0.013)
High Pressure Dummy	-0.608**	1.492**				
	(0.208)	(0.003)				
N	160	160	80	80	80	80
Log Likelihood	-103.669	-222.121	-54.669	-128.215	-47.965	-78.679
LR Chi-Square	10.855	-	1.116	-	3.444	-
Prob>Chi-Square	0.054	-	0.892	-	0.486	-
McFadden R^2	0.050	-	0.010	-	0.035	-

7.3.3 Experience

The effect of experience on broker commissions is taken into consideration in Crellin, Frew and Jud (1988), Glower and Hendershott (1988), and Jud and Winkler (1998). These studies find that experience has a positive effect on the earnings of a broker. The role of a broker is varied and complex. It takes time to learn the proper way to best navigate through the ever changing and uncertain residential real estate environment. Consistent with past studies, we hypothesize a positive relation between experience and broker commissions.

7.3.4 Age

The effect of age on broker commissions has not been addressed in previous studies, possibly because of its expected high positive correlation with experience. However, the correlation coefficient in our dataset between age and experience is not significant. As such, we include this characteristic as a possible explanatory variable and leave the expected sign as an open-ended empirical question[8].

Table 6 Determinants of Broker Commissions

This table reports the results from examining the determinants of broker commissions. The dependent variable is the commission of the broker in the full sample, high pressure, and low pressure samples, respectively. *Male Dummy* is defined as 1=Male; 0=otherwise. *College Degree Dummy* is defined as 1=college degree; 0 otherwise. *Experience* is the number of years the broker has worked in the industry. *Age* is the age of the broker in years. *High Pressure Dummy* is defined as 1=high pressure trials; 0=otherwise. ** indicates a significance level of 99% while * indicates significance at 95%. Standard errors are provided in parentheses.

Variable	Full Sample	High Pressure	Low Pressure
Constant	-6.748	-4.976	-7.030
	(3.927)	(5.080)	(5.371)
Male Dummy	0.145	-2.655	4.371
	(1.598)	(2.190)	(2.240)
College Degree Dummy	-0.478	1.703	-3.466
	(1.746)	(2.364)	(2.408)
Experience	4.495**	4.970**	3.842**
	(0.358)	(0.506)	(0.486)
Age	0.334*	0.271	0.359
	(0.134)	(0.195)	(0.178)
High Pressure Dummy	0.498	-	-
	(1.481)		
N	64	32	32
Adjusted R^2	0.739	0.805	0.741
F-Test	32.928**	27.857**	19.292**

[8] In all of our regressions, we directly test for multicollinearity by examining condition indexes as well as variance inflation factors (VIFs) and tolerance levels. Multicollinearity levels are not an issue in our study, the tests for which are available from the authors upon request.

In Table 6, we consider broker commissions as the dependent variable and broker characteristics as the independent variables. In Model 1, we further include a dummy variable for high versus low time pressure sessions. In Models 2 and 3, we segment the data into high and low time pressure trials, respectively. The two significant variables in Model 1 are broker experience and broker age. Moreover, experience continues to show importance when the sessions are segmented into high versus low time pressure treatments. Consistent with Jud and Winkler (1998), we find that brokers with greater work experience are more likely to match buyers and sellers and earn more commissions. These findings also support the importance of using actual practicing professional brokers as their previous real world experience show relevance in better assisting brokers during time constrained situations.

8. Conclusions

We provide a theoretical model to support our hypotheses that when brokers attempt to match buyers and sellers in a low time pressure environment, they work harder by recommending more homes with different property characteristics to satisfy the stated demand preferences of the buyer. As a result, the degree of matching is significantly increased. As a tradeoff, the search duration in a low time pressure environment is elongated. Interestingly, even though brokers work harder, longer, and are more effective in a low time pressure environment, their income does not significantly differ from their income in a high time pressure environment. Finally, when focusing on earnings, brokers with more experience significantly earn more money than inexperienced brokers. No other demographic characteristic is statistically significant.

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