

Dynamic and static asking prices in the Sydney housing market

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Abstract

This paper investigates the impact of two commonly used asking price strategies on house sales prices. In particular, we compare a dynamic asking price, where the seller adjusts her asking price over time as she fails to sell her property, with a static asking price, where the seller sets an asking price and sticks to it until the property is sold. While this comparison is ambiguous from a theoretical perspective, our empirical study using a comprehensive data set on the properties sold in the greater Sydney region indicates that properties with a dynamic asking price sold, on average, for \$25,400 less than properties with a static asking price, which is approximately four percent of the mean property price in our sample. In addition, we also show that, controlling for the asking price strategy, the duration of sale has a significant impact on sales prices.

Keywords: asking price; dynamic pricing; housing market.

JEL Classification: R31, R32.

1 Introduction

Homes account for a significant proportion of household net worth in countries like Australia and the USA.¹ For most households, the decision to buy or sell a house is likely to be the most significant financial transaction of their lives.

The selling mechanism is amongst the various factors that can influence the outcome of a sale. For instance, the method of sale can affect the time that sellers spend on the market or the price at which they sell their homes. As a result, the selling method can have a significant impact on household's wealth. Not surprisingly, there has been considerable interest in the real estate economics literature in determining what selling strategies may be more successful in terms of higher sale prices.

The existing theoretical literature on the housing market focuses by and large on sellers as the owners of heterogeneous properties who search for potential buyers. This literature typically models buyers as searching for suitable properties having to incur inspection (or search) costs. For example, Chen and Rosenthal (1996a), Chen and Rosenthal (1996b) and Horowitz (1992) examine the behaviour of sellers who advertise an asking price to attract potential buyers who then negotiate with the seller. These authors suggest that the asking price is the upper bound of the transaction price and acts as a commitment device from the seller; a commitment to sell at any price lower than or equal to the asking price. In this literature, the seller's decision entails setting both a static, public asking price and a secret reserve price, which is inferred by buyers in equilibrium.² Carrillo (2012) extends this framework to consider a situation where buyers also undertake a search. He finds an stationary equilibrium in which the asking price is the ceiling price for the negotiations between sellers and buyers. He then estimates the model with the maximum likelihood method and simulates the housing market outcomes when the amount of information and the

¹See for example <http://www.federalreserve.gov/releases/z1/current/z1r-5.pdf> for the USA and <http://www.abs.gov.au/ausstats/abs@.nsf/Latestproducts/> for Australia.

²Chen and Rosenthal (1996b) shows that when buyers arrive one at a time and do not compete with each other, the asking price mechanism is optimal among all other incentive compatible mechanisms. The determination of optimal sale mechanisms is also pursued by Mayer (1995). This author develops a search model to compare auctions with private negotiations. In his model, the choice of asking price affects both the number of arrivals and the distribution of offers. Given the property's characteristics, Mayer (1995) shows that a higher asking price reduces buyers' arrival rate and increases the duration of search. He also suggests that auctions generate higher expected prices than bilateral negotiations in booming markets, with the reverse during a bust. Arnold and Lippman (1995) is another example of comparing two different selling institutions. Finally, Lusht (1996) provides empirical evidence that auctions can generate higher transaction prices than private negotiation.

real estate agent commission change. Carrillo (2012)’s analysis, however, does not consider the possibility of dynamic asking prices and disregards the cases where the asking price is different from the ceiling price. Both of these are pervasive in the real estate industry.

In contrast, Read (1988) and Lazear (1986) provide a rationale for a dynamic asking price, where sellers revise their asking prices if their properties fail to sell at a particular time period. These authors argue that such dynamic asking price strategy may be an optimal response, for example, when sellers learn about the current state of demand in the market.

This paper contributes to the literature by providing a theoretical background that makes it clear that the comparison between static and dynamic asking price strategies, from the point of view of their impact on final transaction prices, is ambiguous.

It follows then that the determination of the optimal asking price strategy is by nature an empirical question. To answer this question, we use a comprehensive data set on properties sold in the greater Sydney region. Our empirical evidence suggests that properties with a dynamic asking price sold, on average, for less than properties with a static asking price. We also show that, controlling for the asking price strategy, the duration of sale has a significant impact on transactions prices³.

Different approaches have been used in the empirical literature to examine the impact of asking prices on transaction prices and time on the market. For example, Yavas and Yang (1995) use a hedonic model to provide evidence that, depending on the value of the properties, asking price may influence the time-on-the-market. Horowitz (1992) considers a framework in which the static asking price posted by the sellers can affect the arrival rate of buyers given the property characteristics. Based on specific functional form assumptions for the distribution of buyers’ arrival, Horowitz (1992) shows that the maximum likelihood estimates of his model yield more accurate predictions than hedonic models.

While most empirical studies focus on the impact of static asking prices on final transaction prices or duration of sale⁴, Knight (2002) examines 3,490 observations in Stockton, California with information about properties with dynamic asking prices. He uses a maximum-likelihood probit model to analyse what determines changes in the asking price. In a similar vein, Knight (2002) provides evidence that properties with atypical characteristics are less likely to be subject a dynamic asking price,

³The potential impact of duration on the final selling prices is well-documented in the literature. See for example Khezr (2014) for a study on the Sydney housing market.

⁴See for example, Haurin (1988), Haurin *et al.* (2010)

while occupancy status (rented versus owner-occupied) of the property and the gap between the initial asking and the revised asking price could increase the likelihood of a price revision. Knight (2002)'s results also suggest that larger revisions in the asking price, on average, result in longer time on the market and a lower selling price. While Knight (2002) attempts to answer why some sellers revise their asking prices, our focus is on determining which of the two asking price strategies result, on average, in higher sales prices. Our empirical approach is also different since we apply a two-stage regression model to overcome the endogeneity problem that arises as the choice of the asking price strategy may not be independent of the characteristics of the property or sale.

This paper is organised as follows. Section 2 presents two competing models of the seller's decision making process when choosing an asking price strategy. Section 3 describes in details the data used in this study and section 4 presents the results. Section 5 concludes.

2 Model

A seller of a property advertises an asking price P_a to attract potential buyers to make offers for her home. The sale takes place over T equal, discrete time periods and for simplicity there is no discounting. The asking price P_a is higher than the seller's true reservation price P_r , which is the lowest price she is willing to sell the property. In this setting, sellers may not want to reveal their reservation prices but instead signal their values through the asking price.

We also assume that the seller's outside value for the property is s . The value of s , for example, may represent an independent valuation of the property. If the seller decides to leave the market at the end of any period, she retains the property at value s . It follows that $P_r \geq s$.

The selling process can be summarised as follows. First, the seller advertises an asking price. Then buyers observe the asking price and decide whether to make an offer to the seller. If there is more than one offer, the seller chooses the highest one. If the seller accepts an offer P , then we refer to P as the transaction price at which she sells her property. Otherwise, she waits for the next round of offers or leaves the market and retain the property at value s . Clearly, $P \geq P_r$.

We do not explicitly model the behaviour of buyers and instead assume that $F(.|P_a)$ describes the conditional distribution of offers made by buyers on the interval $[0, \bar{P}]$ at any period of time. More specifically, $F(P|P_a)$ is the probability that the seller receives an offer P or less given an asking price P_a at any particular period.

Without loss of generality, we assume the seller knows this distribution.⁵

There are a number of variables, which are assumed to be exogenous, that can affect this probability including property characteristics, competition between buyers, and interest rates. The seller, of course, can influence this probability by her choice of the asking price. While in most of the related literature⁶, the asking price is the upper bound of the possible transaction prices (\bar{P}), there is no such restriction in our model. Instead we assume that the transaction price belongs to the interval $[P_r, \bar{P}]$ with $\bar{P} \geq P_a$. Transaction prices that are higher than the asking price arise due to competition between buyers. For instance, if there are two interested buyers with high values, then one of them can make an offer above the asking price.

We impose the following distributional assumptions:

- A.1. Offers are drawn independently at every period according to $F(.|P_a)$, which are independent of time; and
- A.2. Ceteris paribus, a higher asking price decreases the probability of receiving an offer at any particular point in time:

$$\frac{\partial F(P|P_a)}{\partial P_a} < 0$$

- A.3. The probability of having no offer at every period is positive:

$$F(P = 0|P_a) > 0.$$

We now turn to the determination of the optimal reserve price. In our setting, the seller's expected payoff depends on both the asking price and the reserve price. A utility maximising seller chooses these two prices, at any period t , optimally to maximise her overall expected payoff:

$$U_t(P_a, P_r) = \int_{P_r}^{\bar{P}} (P - s) dF(P|P_a) + F(P_r|P_a) U_{t+1}. \quad (1)$$

The solution of this problem depends on a non-trivial way on how we model the time dimension. We will consider two different approaches.

Infinite-horizon

⁵Horowitz (1992) suggests that the theory does not change if the actual distribution is replaced by the realized distribution satisfying the same assumptions and buyers behave strategically.

⁶For instance, see Chen and Rosenthal (1996a), Chen and Rosenthal (1996b) and Horowitz (1992).

Suppose T is very large and it can be interpreted as a infinite-horizon time dimension. This might be appropriate, for example, for the case of sellers who are not in a hurry to sell their properties – perhaps because the property is being rented – and are opportunistically waiting for a large valuation buyer. (See, for example, Horowitz (1992)). In this instance, the optimal search behaviour of the seller is such that the expected payoffs at every period become the same⁷. So the seller’s optimization problem is to choose an asking price and a reservation price which maximises one period’s expected payoff. This would also maximise the sum of per period expected payoffs, which is the total expected payoff. Suppose U^e is the steady state payoff, then we have,

$$U^e(P_a, P_r) = \int_{P_r}^{\bar{P}} (P - s) dF(P|P_a) + F(P_r|P_a)U^e, \quad (2)$$

and therefore,

$$U^e(P_a, P_r) = \frac{\int_{P_r}^{\bar{P}} (P - s) dF(P|P_a)}{1 - F(P_r|P_a)}. \quad (3)$$

Proposition 2.1. *Under an infinite-time horizon, the optimal decision of the seller is to choose the pair (P_a^*, P_r^*) in which $P_r^* = U^e + s$ and P_a satisfies (3).*

Proof. See Appendix.

Proposition 2.1 states that the seller’s optimal behaviour is to post an asking price at the first period, which is kept constant until she sells the object. This type of behaviour is commonly observed in housing markets. As it will be discussed in the next Section, very often sellers do not revise their asking prices even when the property fails to sell for a substantive period of time.

Note that the equilibrium reserve price and the asking price are time invariant because the expected payoff is also time invariant. While our model assumes no discounting, a similar result would hold under positive discounting as the basic underlying idea that (discounted) expected payoffs are constant will continue to hold true.⁸

Finite-horizon

There are several models that analyse the seller’s behaviour when the time horizon is finite⁹. These models typically assume a stopping rule or deadline for a sale to

⁷See Lippman and McCall (1976) for infinite-horizon stationary models.

⁸See Chen and Rosenthal (1996a) for an example with positive discounting.

⁹Read (1988) and Lazear (1986).

occur, and so if a seller is unable to sell her property within that specific time, she leaves the market. This may be an appropriate modelling approach, for example, when a seller has committed to buy a property elsewhere and faces a deadline to sign the purchase contract of her new property. If she cannot sell her home by that time she may withdraw from the market and rent her property instead.

Here we assume that the maximum number of periods in which a particular seller advertises her property is T . If she cannot sell her home by that time she will withdraw from the market and retain the value s for the property. In this case, we show below that both the asking price and the reservation price are time variant. The seller faces a different maximisation problem at each period. At each period $t \in \{1, 2, \dots, T\}$, the seller's expected payoff is,

$$\Pi_t = \int_{P_{rt}}^{\bar{P}} (P - s) dF(P|P_{at}) + F(P_{rt}|P_{at}) \Pi_{t+1}. \quad (4)$$

Proposition 2.2. *Under a finite-time horizon, the optimal reservation price at every period $t < T$ is equal to, $P_{rt}^* = s + \Pi_{t+1}$.*

Proof. Appendix.

The above proposition states that the optimal reserve price at any period $t < T$ is equal to the seller's outside value for the property plus the expected payoff for the next period. This is a standard result for this type of model. To be able to make inferences about expected sales prices, however, we need to further investigate the sequence of reserve prices from the first period until the final period. The following corollary shows that the optimal reserve price decreases over time.

Corollary 2.1. $P_{rt}^* > P_{rt+1}^*$.

Proof. Appendix.

Thus, the seller starts with a high reserve price at period one and reduces it over the time if she fails to sell the property at each period. This implies that the expected payoffs decrease over the time. In fact, we show that if the seller fails to sell until the last period, she sets a final-period reserve equal to the outside value for the property. To see this, note that we can write the final period's expected payoff as:

$$\Pi_T = \int_{P_{rT}}^{\bar{P}} (P - s) dF(P|P_{aT}) + F(P_{rT}|P_{aT}) \Pi_{T+1}. \quad (5)$$

It is straightforward to check that the first order conditions to maximise (5) implies a final-period optimal reserve price which is equal to the seller's value as the net payoff at period $T + 1$ is zero. This is summarised by the following lemma.

Lemma 2.1. *The optimal reservation price at the final period is equal to s .*

Having characterised the optimal reserve price for both finite and infinite time horizons, we now focus on setting the optimal asking prices. This is however, trivial, given that the asking price and reserve prices are linked through the distribution $F(.|.)$.

This, in turn, suggests that the optimal asking price will depend on how we model the time dimension. Under an infinite-time horizon, the optimal asking price will be constant over time. Under a finite-time horizon, the optimal asking price will decrease over time. However, there is no a priori reason for selecting either model. Moreover, both asking price strategies are commonly observed in practice. This ambiguity is the key motivation for our paper, which aims to provide some light on the choice of asking prices by sellers and the impact of these choices on final prices (and, consequently, on expected payoffs).

3 Data

The data includes 28,244 properties which have been sold in the Sydney region in Australia, including all completed transactions in the calendar year of 2011. For each property, we observe location and over twenty different characteristics. In this study we focus on the characteristics that are commonly used in the literature, namely number of bedrooms, bathrooms, type of property (house or unit), parking and geographic location.

The data also includes the first date when each property was first advertised and the initial asking price. The final date in which the property was in the market and the final advertised price are also observed. Furthermore, the transaction price and transaction date are recorded for each property. The data shows the properties that have been sold in the calendar year 2011. Therefore, it is possible that there are properties that had been advertised in the previous year but sold in 2011. Similarly, there will be properties that were advertised in 2011 but sold later and, therefore, are not included in the data. Our analysis assumes that one calendar year is the maximum time in which a property will be in the market and, given the sample size, we are confident that the data captures enough variation so that we can meaningfully

distinguish between properties that took long to sell or that sold quickly.¹⁰

We divided the data by geographic location into the following six regions: Sydney central business district and the lower north shore, eastern suburbs, inner west, upper north shore and the northern beaches, west and south western suburbs and finally St George and Sutherland shire. For more information regarding each region and their postcodes please refer to Appendix A. These geographical regions include fairly similar suburbs to control for the location differences between properties. This classification is standard in the real estate industry in Sydney.¹¹ Table 1 provides some of the key descriptive statistics of the data.

Table 1: Data Summary

	Mean	Median	Max.	Min.	Std. Dev.
Price (thousand \$)	604.36	513.77	16450.00	107.00	469.02
Property Type (House = 1, Unit = 0)	0.51	1	1	0	0.49
Bedrooms	2.66	3.00	8.00	1.00	1.02
Bathrooms	1.53	1.00	8.00	1.00	0.66
Parking	1.36	1.00	6.00	0.00	0.77
Balcony	0.33	0.00	1.00	0.00	0.47
Study	0.12	0.00	1.00	0.00	0.32
Ensuit	0.22	0.00	1.00	0.00	0.41
Number of observations in Region 1			3,057		
Number of observations in Region 2			1,381		
Number of observations in Region 3			3,401		
Number of observations in Region 4			3,954		
Number of observations in Region 5			12,760		
Number of observations in Region 6			3,691		
Properties with dynamic asking price			11,898		
Number of observations			28,244		

Table 1 shows that the number of properties sold vary across regions. The reason for this is that, as we discussed earlier, the regions are determined by suburbs characteristics rather than by geographic area and number of properties. For instance,

¹⁰Since we sample properties with completed transactions, the properties that are still active in the market at the end of the year 2011 will not be in our sample. In fact, at any point of time there are some properties which are active in the market. However, this does not result in sample selection bias since we capture those properties that have been advertised in the year before and completed their transaction in 2011.

¹¹For example, see www.domain.com.au.

eastern suburbs (Region 2) are characterised by luxury dwellings within short distance to famous beaches and the Sydney’s CBD. We use each region as a dummy in our empirical analysis to reduce heterogeneity between suburbs. Properties have been divided into two categories in terms of their types: houses and units. Units or apartments are usually located in a complex with more than one level. Houses and Town-houses, which are considered in the same category, have similar characteristics such as backyard and secure garage.

Finally, over forty percent of sellers (11,898 sellers) updated their asking price during the period when the dwelling was advertised. This variation in the data will allow us to explore the returns from the two different pricing strategies that we have identified in the previous section.

4 Empirical analysis

Our empirical analysis is designed to investigate the effect of the two alternative asking price strategies—identified in Section 2—on the final selling price of properties. With this in mind, we divided sellers into two groups according to whether or not they have updated their asking prices.

We define a dummy variable that takes value of one if the seller uses a dynamic asking price. Of course, the price strategy is itself endogenous, and it is not possible to observe what would have happened to the final sales price if a particular seller had used a constant asking price rather than a dynamic asking price. Endogeneity, then, can result in selectivity bias because the conditional expectation of the error terms are non-zero, specially if there are some omitted price affecting variables. See, for example, Lusht (1996).

To overcome potential selectivity bias, we use the method introduced by Heckman (1979). This approach entails following two steps. First, we run a probit regression with the endogenous variable (the dummy price strategy) as the dependent variable and property characteristics, duration dummies and the location dummies as independent variables. The outcome of the probit regression (generalized and ordinary residuals) is used to construct the selectivity variable, which is given by the inverse of the Mills ratio or the *hazard rate* function¹². We use the generalised, ordinary and actual fitted residuals to form the Mills ratio¹³. The use of the selectivity vari-

¹²The *hazard rate* function of a distribution is: $h(x) = \frac{f(x)}{1-F(x)}$, where F is the cumulative distribution function and f is its density function.

¹³Mills = $\frac{G(1-F)}{f}$, where G is the generalised, F is the fitted and f is the ordinary residuals.

able in the second-stage of estimation, which is a hedonic regression, eliminates the selectivity bias¹⁴.

Three dummy variables are included in this regression to control for sale duration. The variable *4 Weeks* is equal to one if sale duration is less than four weeks and zero otherwise. Similarly, the variable *8 Weeks* is equal to one if the property was sold within four to eight weeks and zero otherwise. Finally, the variable *12 Weeks* is equal to one if the property was sold within eight to twelve weeks and zero otherwise.

More specifically, the first stage regression model is given by:

$$PS_i = \alpha_0 + \beta_0 X_i + \gamma_0 D_i^n + \psi_0 L_i^m + \epsilon_i,$$

where α_0 is the intercept and X is a vector of the property characteristics listed in Section 3 (e.g., whether it is a house or a unit, or the number of bedrooms and bathrooms). D s are the dummy variables for the duration of time in which the property was in the market until being sold. L s are the location dummies and ϵ is the error term. The outcome of this model is used to build the selectivity variable for the second-stage estimation.

In the second-stage, we run the following linear regression model.

$$P_i = \alpha + \beta X_i + \gamma D_i^n + \psi L_i^m + \theta A_i + \delta PS_i + \xi SV_i + \varepsilon_i \quad (6)$$

A is the initial asking price and PS is the asking price strategy dummy variable. Finally, SV is the selectivity variable and ε is the error term capturing unobserved variables. We run two regressions; one with the selectivity variable and one without it to assess the impact of the potential selectivity bias on estimated coefficients. To conclude, we also run another similar two-step model but without duration dummies to investigate the effect of duration on the price strategy.

5 Results

As discussed above, we first run a probit model in which the dependent variable takes a value equal to one if the asking price strategy was dynamic and zero otherwise. Table 2 shows the result of the probit estimation. Recall that the key role of the results from the probit regression is to allow us construct the selectivity variable. Note also that most coefficients are significant at the 1% level, including the log-likelihood of this model.

¹⁴Lee (1982).

Table 2: Probit model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Constant	-0.284	0.035	-8.095	0.000
Property Type	0.087	0.023	3.686	0.002
Bedrooms	0.079	0.013	5.979	0.000
Bathrooms	-0.095	0.016	-5.660	0.000
Parking	-0.022	0.012	-1.849*	0.064
Balcony	0.106	0.018	5.712	0.000
Study	0.132	0.024	5.354	0.000
Ensuite	0.137	0.021	6.350	0.000
4 Weeks	-0.935	0.022	-40.766	0.000
8 Weeks	-0.177	0.019	-9.186	0.000
12 Weeks	0.299	0.023	12.727	0.000
Region 1	0.127	0.032	3.867	0.000
Region 2	0.070	0.041	1.676*	0.093
Region 3	0.082	0.031	2.625	0.008
Region 4	0.039	0.030	1.305**	0.191
Region 5	0.127	0.024	5.124	0.000
Log likelihood	-17,799.68			
Obs with Dependent var. = 0	16346	Total obs	28244	

* Significant at the %10 level.

** Not significant at %10 level.

‡All other variables significant at the 1% level.

The next stage is to construct the selectivity variable from the results of the probit model. As explained in the previous section, we use the selectivity variable in our hedonic regression to overcome a potential selectivity bias. Table 3 shows the result of the second-stage estimation with and without the selectivity variable. All coefficient for the property characteristics have the expected signs. The results with the selectivity variable surprisingly have higher level of significance specially for duration dummies. The significance of the selectivity variable suggests it is important to control for this and the inclusion of the selectivity variable could account for some part of the selectivity bias problem.

Our focus, however, is on the coefficient of the price strategy dummy (PS dummy). The results suggest that the pricing strategy matters and properties with dynamic asking price have lower average transaction prices. These properties sold, on average and *ceteris paribus*, for \$25,400 less than properties with a static asking price.

Therefore, sellers benefit by not changing their asking prices. There are different

Table 3: OLS regression, dependent var. transaction price.

Variable	With selectivity var.		Without selectivity var.	
	Coefficient	t-statistics	Coefficient	t-statistics
Constant	-116.2	-2.35	37.28	5.08
PS dummy	-25.4	-7.43	-25.7	-7.51
Asking price	0.78	174.8	0.78	175.6
Property type	31.2	5.43	21.9	4.45
Bedrooms	23.1	6.25	15.5	5.55
Bathrooms	21.0	5.68	26.3	7.92
Parking	0.80	0.31**	2.85	1.13**
Balcony	13.7	2.46*	0.99	0.26**
Study	20.7	2.97	5.93	1.14**
Region 1	64.5	7.95	51.3	7.39
Region 2	46.3	5.13	39.5	4.51
Region 3	17.9	2.55*	9.27	1.43**
Region 4	24.8	3.88	20.6	3.30
Region 5	-30.2	-4.56	-43.4	-8.44
4 Weeks	-102	-3.05	1.95	0.43**
8 Weeks	-17.0	-2.39*	1.12	0.27**
12 Weeks	25.7	2.54	-1.84	-0.36**
Selectivity Var.	151	3.14		
R^2	0.66		0.66	
DW	1.98		1.98	

* Significant at the 5% level.

** Not significant at the 10% level.

‡ All other variables significant at the 1% level.

† PS dummy is one if the asking price is dynamic.

potential explanation for this result. For example, a dynamic asking price strategy could entail setting a higher than average initial asking price. As we suggested in our theoretical model, a higher than average asking price, *ceteris paribus*, reduces the probability of receiving offers. It is plausible that some sellers may benefit from setting a higher reserve (and, therefore, successfully signalling some unobserved positive characteristics of the property). However, our empirical results suggest that, on average, this strategy does not pay off because the marginal cost of a higher than average asking price (i.e., the foregone offers) is greater than the marginal benefit (the value of signalling the unobserved characteristics of the property).

Controlling for the asking price strategy, duration of sale turns out to have a significant impact on transactions prices. In particular, if a seller who sells her

property within the first month were instead to wait another four weeks, her expected transaction price would increase by \$85,000. On average, controlling for the asking price strategy, waiting for another month increases the average transaction price by \$32,700. This corresponds to approximately 5% of the average sale of properties.

The coefficients on region dummies provide clear confirmation that the geographical classification by real estate agencies captures the diversity in the market place. While Region 1 (Sydney CBD and lower north shore) attract the highest sale prices, Region 5 (west and south western suburbs) has the lowest transaction prices.

Finally tables 4 and 5 show the results for a two-stage estimation where we omitted the duration dummies. As it can be observed, the impact of such omission on the coefficients of all variables is small and the Durbin-Watson test suggests that there is no autocorrelation in the results reported on Tables 2 and 3. It confirms that the significant impact of duration on transaction price is not caused by correlation between the duration and the property characteristics.

Table 4: Probit model without duration dummies

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Constant	-0.549	0.032	-16.78	0.000
Property Type	0.088	0.023	3.858	0.000
Bedrooms	0.084	0.012	6.527	0.000
Bathrooms	-0.069	0.016	-4.240*	0.000
Parking	-0.026	0.011	-2.302	0.021
Balcony	0.123	0.018	6.80	0.000
Study	0.159	0.024	6.617	0.000
Ensuite	0.173	0.021	8.213	0.000
Region 1	0.155	0.032	4.846	0.000
Region 2	0.092	0.040	2.270*	0.023
Region 3	0.116	0.030	3.831	0.000
Region 4	0.063	0.029	2.159*	0.030
Region 5	0.171	0.024	5.124	0.000
Log likelihood		-19,014.54		
Obs with Dependent var. = 0	16346	Total obs		28244

* Significant at the %5 level.

‡All other variables significant at the 1% level.

Table 5: Second-stage regression without duration dummies

Variable	With selectivity var.		Without selectivity var.	
	Coefficient	t-statistics	Coefficient	t-statistics
Constant	-127.7	-2.68	38.2	5.54
PS dummy	-25.8	-7.86	-26.3	-8.03
Asking price	0.78	174.8	0.78	175.6
Property type	30.5	5.50	21.9	4.45
Bedrooms	22.9	6.55	15.5	5.55
Bathrooms	24.9	7.48	26.2	7.90
Parking	0.59	0.23**	2.86	1.14**
Balcony	14.6	2.68*	0.93	0.24**
Study	22.5	3.21	5.87	1.13**
Region 1	65.9	8.14	51.3	7.38
Region 2	47.7	5.26	39.5	4.51
Region 3	20.4	2.83	9.19	1.42**
Region 4	26.6	4.11	20.6	3.30
Region 5	-27.3	-3.95	-43.5	-8.47
Selectivity Var.	138	3.52		
R^2	0.66		0.66	
DW	1.98		1.98	

* Significant at the 5% level.

** Not significant at the 10% level.

‡ All other variables significant at the 1% level.

† PS dummy is one if the asking price is dynamic.

6 Concluding Remarks

The decision to buy or sell a house or a unit is one of the most important financial decisions at the household level. The family home accounts for a large share of household wealth in many developed economies. It follows that the selling method can have a significant impact on household's wealth, and as a result, it can impact on other life-changing decisions such as when to retire, when to downsize or whether it is possible to move between suburbs, for example, to take advantage of better schools for the children. Not surprisingly, there has been considerable interest in the real estate economics literature in determining what selling strategies may be more successful in terms of higher sale prices.

This paper fills a gap in the literature by comparing two commonly used selling strategies: dynamic versus static asking prices. From a theoretical perspective, the comparison of these two strategies in terms of expected sales price is ambiguous.

However, we present robust evidence that a dynamic asking price is associated with a lower sale price in the Sydney housing market. Our empirical results also highlight that the duration of the sale, perhaps as a proxy for the quality of the match between buyers and sellers, is an important determinant of transaction prices. On average, waiting another month to sell the property would add \$85,000 to the sales price, or approximately 14% of the average property values.

7 Appendix

7.1 Appendix A

- Region 1
 - Sydney CBD (Post Code 2000-2016, City- Redfern)
 - Lower North Shore (2060-2090, North Sydney - Cremorne)
- Region 2
 - Eastern Suburbs (2017-2036, Waterloo - Matraville)
- Region 3
 - Inner West (2037-2050, Glebe-Camperdown)
 - Gladesville-Ryde-Eastwood (2110-2126, Hunters Hill - Cherrybrook)
- Region 4
 - Upper North Shore (2070-2087, Linfield-Forestville)
 - Northern Beaches (2092-2107, Seaforth-Avalon)
- Region 5
 - Western Suburbs (2127-2148, Homebush Bay - Blacktown)
 - Parramatta-Hills District (2150-2159, Parramatta - Galston)
 - South Western Suburbs (2160-2214, Merrylands - Milperra)
- Region 6
 - St George (2216-2227, Rockdale-Gymea)
 - Sutherland Shire (2228-2234, Miranda - Menai)

7.2 Appendix B

Proof of Proposition 2.1

The first order condition is given by:

$$\begin{aligned} \frac{\partial U^e}{\partial P_r} = & -[f(P_r|P_a)(P_r - s)](1 - F(P_r|P_a))^{-1} \\ & + f(P_r|P_a)(1 - F(P_r|P_a))^{-2} \int_{P_r}^{\bar{P}} (P - s)dF(P|P_a) = 0. \end{aligned} \quad (7)$$

After some cancellation it becomes,

$$(P_r - s)(1 - F(P_r|P_a)) - \int_{P_r}^{\bar{P}} (P - s)dF(P|P_a) = 0. \quad (8)$$

Suppose the second order condition for maximisation is satisfied. Then the optimal reservation price must satisfy,

$$P_r^* = U^e + s. \quad (9)$$

Substituting 9 into 8 yields:

$$P_r^* - s = \frac{\int_{P_r^*}^{\bar{P}} (P - s)dF(P|P_a)}{1 - F(P_r^*|P_a)}. \quad (10)$$

The other first order condition is given by $\frac{\partial U^e}{\partial P_a} = 0$, that is:

$$\int_{P_r}^{\bar{P}} (P - s)dF_{P_a}(P|P_a)(1 - F(P_r|P_a)) + f_{P_a}(P_r|P_a) \int_{P_r}^{\bar{P}} (P - s)dF(P|P_a) = 0, \quad (11)$$

which becomes:

$$\int_{P_r}^{\bar{P}} (P - s)dF_{P_a}(P|P_a) + f_{P_a}(P_r|P_a)U^e = 0 \quad (12)$$

The pair (P_a^*, P_r^*) is the one which satisfies (10) and (12) simultaneously. □

Proof of Proposition 2.2

We have,

$$\frac{\partial \Pi_t}{\partial P_{rt}} = -(P_{rt} - s)f(P_{rt}|P_{at}) + f(P_{rt}|P_{at})\Pi_{t+1} = 0, \quad (13)$$

and therefore,

$$P_{rt}^* = s + \Pi_{t+1}$$

It is easy to check that as long as $f(\cdot)$ function is non-increasing the second order condition is also satisfied. \square

Proof of Corollary 2.1

Since P_{rt} is the lower bound of the expected profit, at every period t we have, $P_{rt} \leq \Pi_t$. Thus it follows that

$$P_{rt+1}^* \leq \Pi_{t+1} < \Pi_{t+1} + s = P_{rt}^*$$

\square

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