Are Lucky Prices Optimal?

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This study is made possible by the generous provision of data from Sirca and CoreLogic. We thank George Blazenko and Meir Statman for their suggestions on the paper, as well as Eleonora Monaco, Geoffrey Poitras, Amir Rubin, David Simmons, and seminar participants at the Beedie School of Business at Simon Fraser University and the University of Chieti-Pescara for their comments. The co-operation from CoreLogic and Sirca in data provision is also acknowledged. Any errors remain the authors' responsibility.

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Abstract

This is the first study to analyze the influence of culture and luck in housing market price setting decisions and the subsequent sale outcomes. We show that 'lucky 8' price endings are more likely to be chosen than other uncommon price endings by sellers in markets with a high proportion of Asian-background migrants. Unfortunately, however, using regression and hazard models we find that the use of lucky price endings leads to worse sale outcomes. Common price endings, 9 and 5, result in greater price discounting, while uncommon price endings are associated with negotiation premiums and shorter selling times.

Introduction

Decisions involving buying and selling houses are the most significant decisions that most individuals will make in their lifetime, financially if not also emotionally. Well-developed rational economic models developed in the literature propose optimal strategies for buyers and sellers. In particular, the literature has focused on the strategic role of list prices (Yavas and Yang 1995; Arnold 1999). Yet, little work on how individuals set and respond to list prices incorporates behavioral economics and the role of individuals' cultural beliefs. This paper is the first to examine one key component that may affect buying and selling behavior: the presence of lucky numbers in the property's list price.

To our knowledge, the only price setting paper that considers cultural factors is found in the consumer marketing literature. Simmons and Schindler (2003) find that culture influences price setting – specifically that the 'lucky number 8' is commonly used in Chinese consumer products – but demonstrate that culturally significant price endings are used only for relatively cheap products. Houses are substantially more expensive than consumer products, yet behavioral biases are also documented in housing markets (Salzman and Zwinkels 2017).

Using data from Sydney, Australia, this paper builds on previous list price setting research to study how cultural factors persist in a highly multicultural setting. Census data are used to identify a 'High Culture' (*HC*) subsample of listings in suburbs with significant populations of immigrants from countries with encultured preferences stemming from cultural beliefs that associate the number 8 with luck. We show that there is a persistent pattern in property list price endings that reflects these cultural preferences. Across all listings, price endings cluster at 9 and 5. However, in the *HC* subsample, significant clustering in list prices also occurs at 8. We argue that this is a lucky price ending used to target prospective buyers. In contrast to the findings of Simmons and Schindler (2003), we find that the use of lucky price endings is not affected by the relative quality of the property. Relative quality nevertheless affects the use of 'just below' pricing – that is, prices that are just below a round digit ending. We show that higher priced properties are more likely to list at round price endings while lower priced properties are more likely to list at just below price endings.

Interestingly, the 8 price ending is found to have little positive impact on sale outcomes, as it does not improve the likelihood of a sale, improve the sale price or decrease the listing time of the property. In *HC* and non-*HC* areas, the most common price endings (9 and 5) are found to negatively affect sale prices through sale-to-list-price discounting (*SLPD*), supporting the conclusions of Beracha and Seiler (2014). Uncommon and 0 price endings are associated with a negotiation premium. That is, where the *SLPD* is negative, reflecting higher buying intensity. Further, after controls for other sale and property factors are included, uncommon endings are found to have the greatest effect in decreasing time on market (*ToM*).

In the next section, we bring together strands of the marketing, psychology and real estate literature. The research gaps that are identified form the basis for our formal hypotheses. We then describe the methodology used to identify list price endings and to subsequently test our hypotheses. The final sections present the data and results before we conclude with a discussion of how this paper can influence future research and practice.

Literature review and hypothesis development

Price setting decisions are studied extensively in the marketing discipline in relation to retail consumer products. The consistent finding is that price endings have an economically disproportionate impact on sale outcomes. Specifically, sellers maximize revenue by setting a high price ending, and consequently, advertised price endings – the right-most digit – are found to cluster at 9. Prices ending in 9 are frequently referred to as just below values. Other documented common price endings are 5 and 0, where their popularity is attributed to the cognitive ease or processing round numbers.

Recently, price ending research has extended to the housing market. Palmon, Smith and Sopranzetti (2004) find clustering in list prices at just below endings. However, the just below endings in that study are associated with longer selling times and lower sale prices. By contrast, Allen and Dare (2004) observe a positive relationship between the use of just below endings and sale prices. These conflicting results are studied by Beracha and Seiler (2014). Consistent with earlier findings, they find significant clustering at round and just below numbers and, in support of the findings of Palmon, Smith and Sopranzetti (2004), conclude that just below prices attract greater *SLPD* than alternative price endings. All these papers use samples of sales from US suburbs. We are the first to extend this literature beyond the U.S. and to use a substantially larger dataset. Our unique dataset also includes listings that result in sales and those that fail to sell, thus avoiding the sample selection bias inherent to earlier research.

Furthermore, no prior research has examined whether cultural beliefs and biases influence price setting decisions in residential real estate. An emerging literature examines how psychology and culture interact in multicultural housing market decisions with regard to property attributes (Fortin, Hill and Huang 2014; Agarwal et al. 2016). In this paper, we fill this niche and contribute to the broader research gap regarding the influence of cultural factors on economic behavior identified by Ackerman and Tellis (2001).

The real estate buyer-seller search model

Housing is an illiquid, spatially fixed and highly heterogeneous asset. Prospective buyers have heterogeneous demand preferences for property attributes, while sellers face uncertainty regarding the number of buyers and their preferences. As such, classic models of residential real estate buyer and seller behavior are typically applications of Stigler's (1961) economic search theory.

A broadly accepted outcome of the residential real estate search model is the trade-off between sale price and *ToM*. That is, the profit-maximizing seller aims to maximize the sale price while minimizing costs. However, search theory predicts that the potential sale price is monotonically increasing with time as more prospective buyers place offers, while the costs associated with listing the property are also positively related to time.

Empirically, the price-time relationship is more complex, and endogeneity between property attributes and the sales process is well documented: more expensive properties (Miller 1978) and more atypical properties (Haurin et al. 2010) are found to take longer to sell than relatively cheaper and common properties. A more recent extension of residential real estate sales processes and property endogeneity is the choice to sell via auction or negotiated sale. While many early papers on this topic document the expected trade-off between the sale price and *ToM* (an excellent review of the literature is provided in Quan (1994)), Frino, Peat and Wright (2012) show that endogeneity also exists in the property quality and sales mechanism decision.

In the choice to sell by negotiated sale, a major decision faced by the property sellers is the choice of list price. List prices have a dual role when market participants are assumed to be rational, in influencing the number of buyer offers received and setting a reference point for price negotiations.

Arnold (1999) focuses on the whether lower or higher list prices are optimal. He argues that, all else being equal, a lower (higher) listing price positively (negatively) influences the rate at which offers from prospective buyers arrive, and (ii) a higher (lower) list price leads to a higher (lower) initial offer price in subsequent buyer-seller negotiations. When the bargaining position of the parties is considered, his results show that the seller’s optimal strategy is to set a high initial list price. This result is consistent with evidence of a positive relationship between list prices and sale prices, both where the list price is treated as a ceiling (Yavas and Yang 1995) and where there is no restriction on the price negotiation direction[2] (Han and Strange 2016).

[2] Note the important difference between list prices for residential real estate and ask prices in other asset classes and consumer markets. A prospective buyer may view the list price as a

While the high initial list price strategy is expected to increase *ToM*, Arnold (1999) shows that an impatient seller has an option to lower their asking price. In empirically demonstrating this behavior, Merlo and Ortalo-Magné (2004) argue that the list price also carries important signaling information about the quality of the property. This is an important development in the literature, as it incorporates the buyer's search problem into the seller's price setting decision. Indeed, sellers who convey additional information to buyers can reduce search times for buyers who most highly value the property's characteristics. This supports earlier findings by Anglin, Rutherford and Springer (2003).

The rational strategic and signaling theories of list prices discussed above do not account for cognitive processing limitations and behavioral factors that affect both sellers and buyers. Research that considers the behavioral role of list prices is reviewed next with a focus on 'charm' pricing and relevant literature from the marketing discipline.

Behavioral real estate and price endings

As a further avenue for advancing the behavioral real estate literature, research on list prices has presented opportunities for researchers to examine the cognitive biases and limitations of both sellers and buyers. For example, Genesove and Mayer (2001) and Bucchianeri and

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starting negotiation from which to bargain to a lower eventual sale price. By contrast, and in a more supply-constrained housing market, prospective buyers may aim to outbid one another, which may push the eventual sale price higher than the list price. In this way, residential listing prices are not necessarily ceilings on the final transaction value.

Minson (2013) use list prices to demonstrate the presence of loss aversion and anchoring effects, respectively. A comprehensive review of the behavioral real estate literature is provided in Salzman and Zwinkels (2017).

The choice of numbers which make up a price are also linked to behavioral biases. Allen and Dare (2004) study the effect of just below pricing on real estate sale prices. The authors find evidence that properties listed for sale using the just below device (which they define as list prices ending in \$500, \$900, \$4,900, \$9,000 and \$9,900) result in higher sale prices, which is consistent with research from the marketing literature showing the 9 price ending results in higher sales and buyer demand (see, for example, Anderson and Simester 2003).

Price ending research in consumer goods has attracted attention over many decades in the marketing literature. A common finding in studies based in North America is that the asking prices for consumer goods cluster at round number (0 and 5) and just below (9) endings. For a recent paper in this area, which includes a summary of the large body of earlier research, see King and Janiszewki (2011). Simmons and Schindler (2003) examine the role of culture in price setting decisions and analyze price endings in several Asian markets. Using advertised prices for consumer goods in Shanghai, Hong Kong and Taiwan, the authors identify the most common price ending to be 8. The number 8 in Chinese culture is perceived as incredibly lucky, owing to its homonymic relationship to the Cantonese and Mandarin words for “fortune” (Ang 1997). They conclude that price ending patterns are not universal, as their evidence indicates that price endings are chosen to reflect the target buying population.

An application of this cultural bias is documented in property address numbers for real estate in China, Hong Kong, Singapore and Canada (Agarwal et al. 2016; Shum, Sun and Ye 2014; Fortin, Hill and Huang 2014; Chau, Ma and Ho 2001). A common finding is that apartments on the 8th floor or with 8 in the street number attract a sales price premium. In a comprehensive analysis of property and buyer characteristics, Agarwal et al. (2016) document that age and prior misfortune are positively related to superstitious behavior. By contrast, the present paper considers seller behavior, specifically sellers' determination of listing prices. Of the emerging body of studies that has researched clustering in real estate listing and sale prices, none have considered whether the preference for culturally lucky numbers exists.

Pope, Pope and Sydnor (2015) demonstrate that property sale prices tend to cluster at round numbers and claim that this finding supports the role of focal points in bargaining and negotiation outcomes. A small part of their paper considers whether the sale price clustering is due to list price setting. Pairing a small subset of their transaction data to listing information from a sample of Chicago-based sales, the authors observe some level of price clustering in list prices at round numbers.

Palmon, Smith and Sopranzetti (2004) provide a more in-depth consideration of list price ending choices and sale outcomes. Using transaction data for a suburb in Houston, Texas, between 1992 and 1995, the authors compare round endings to just below endings, and they find that listings with just below endings are more frequently chosen than listings with round endings or other price endings. However, listings with just below endings also take longer to sell and result in a lower quality-controlled sale price than even ending listings. This result is questioned by Allen and Dare (2004), who observe a positive relationship between the use of just below endings and sale prices.

Beracha and Seiler (2014) empirically investigate this conflict by using a sample of transactions between 1993 and 2011 in Hampton Roads, Virginia. The authors conclude that just below prices attract the greatest *SLPD*, which provides some support for the results of Palmon, Smith and Sopranzetti (2004). Beracha and Seiler (2014) show that some of the results in Allen and Dare (2004) may arise from their failure to control for the degree of overpricing that the list price itself carries.

A major limitation in these previous studies is that their samples are restricted to listings with sale outcomes. Such a restriction raises possible sample selectivity issues, as both *ToM* and *SLPD* is observed conditionally on the property selling. Our paper is the first to include listings that do not sell in order to consider how price endings affect the likelihood of a sale. Further, no prior research has examined whether cultural beliefs influence price setting decisions and outcomes in real estate.

Hypothesis development

Drawing on the findings of previous research, we now develop a set of testable hypotheses to determine whether an optimal price ending rule exists. Three price ending cluster types are observed in the literature. The first type is the round number endings of 0 and 5. Round numbers have a higher degree of cognitive accessibility than other numbers, meaning that they are computationally easier to process and thus linked to the cognitive limitation and heuristics literature in behavioral economics.

The second type of price setting strategy uses just below pricing. In an experimental setting, Bizer and Schindler (2005) show that “consumers ignore, or give very little attention to, the ending digits of a price” (Bizer and Schindler 2005: 772) owing to a ‘drop-off’ effect, where consumers consider only the left-most digits important. This cognitive bias results in an underestimation of the actual price. Considering this drop-off effect, the profit-maximizing seller will choose the highest right-most value as such a strategy maximizes her economic value for the same perceived cost by the buyer.

The final price ending that we consider links cultural preferences for certain numbers to decision making and biased judgment. Simmons and Schindler (2003) argue that numbers perceived as lucky in some Asian cultures, particularly the number 8, are more frequently used to attract prospective buyers. We refer to prices that appeal to the specific cultural beliefs of a subset of the population as ‘culturally significant’ and are an application of cultural cognitive bias (Hoff and Stiglitz 2016).

In line with the findings of other price endings studies, we hypothesize that price endings cluster across all property listings at round and just below endings. Our first hypothesis is thus as follows:

Hypothesis 1: Compared with other numbers, 5 and 9 are the most frequently used price endings.

Evidence in support of this hypothesis will be consistent with that of similar house price listing studies by Beracha and Seiler (2014), Palmon, Smith and Sopranzetti (2004) and Pope, Pope and Sydnor (2015). These papers, however, limit their analysis in assuming a universal pattern of price endings and homogenous cultural preferences across prospective buyers regarding numbers. By contrast, the marketing literature indicates that price endings do not follow a universal pattern but are set to have the highest appeal to the target population of prospective buyers. Simmons and Schindler (2003) find that in several Asian markets, the most common price ending for consumer goods is 8, followed by 5, 9 and 0. We expect to find that sellers choose list prices that they believe will optimize sale outcomes and that this will be influenced by the cultural preferences of prospective buyers.

Price clustering at auspicious numbers is shown to occur in a number of Asian equity markets (Brown and Mitchell 2008; Brown, Chua and Mitchell 2002). In research on residential real estate markets, no previous attention has been devoted to cultural influences on list prices. However, a large literature that identifies a price impact from auspicious numbers in street addresses in Asian markets has emerged (Agarwal et al. 2016). These findings have been shown to extend to Western markets with high Chinese migrant populations, such as Vancouver, Canada (Fortin, Hill and Huang 2014). Our next hypothesis explores whether cultural biases influence property list price setting:

Hypothesis 2: Culturally significant price endings are used to appeal to relevant target buyers.

Evidence in support of this hypothesis would indicate that sellers are cognizant of the preferences of their target buyers, which is consistent with the findings of Simmons and Schindler (2003), and set their list prices accordingly.

Simmons and Schindler (2003) also demonstrate that the use of the 8 price ending in consumer goods is negatively related to the relative price of the good. That is, the frequency at which 8 as a price ending occurs is higher (lower) for cheaper (more expensive) products. The relationship between other common price endings and the relative price of consumer goods, however, shows that just below price endings are used more frequently for higher priced goods (Schindler and Kirby 1997).

The relationship between list price endings and property value in residential real estate markets is previously unexplored. Thus, to determine whether these patterns between price endings and relative value documented in the marketing literature extend to real estate, we propose the following hypotheses:

Hypothesis 3a: Just below price endings are more common among relatively more valuable properties.

Hypothesis 3b: Culturally significant price endings are less common among relatively more valuable properties.

While the hypotheses so far focus on list price setting decisions, we further aim to determine the sale outcome of using particular list prices. From the preceding literature review, it is well established that sellers face an optimization problem to maximize the selling price while minimizing *ToM*. Embedded in the seller's strategy is the option to accept an offer (and achieve a sale) or reject it and wait for a higher offer.

A limitation in earlier work by Palmon, Smith and Sopranzetti (2004) and Beracha and Seiler (2014) is that they truncate their samples to exclude property listings that do not sell. That is, they capture only listings that successfully result in a transaction. Thus, questions regarding the effectiveness of list price choices in achieving a sale remain open. We expect that sellers are more likely to accept a sale when they have a larger pool of offers to select from. As the marketing literature shows that round number, just below and culturally significant endings are effective in attracting prospective buyers, our next hypothesis is as follows:

Hypothesis 4: The use of 5, 9 and, in *HC* areas, 8 price endings increases the likelihood of a property sale, all else being equal.

The final set of hypotheses explores the impact of list prices on two aspects of sale outcomes: (i) the final price achieved, and (ii) the selling time. We first explore the apparent conflict in the literature surrounding price endings and price impact and extend it to also consider the case where culturally significant price endings are used. Specifically, we expect to find, in line with Beracha and Seiler (2014), that just below prices lead to higher *SLPD* than other price endings. While Simmons and Schindler (2003) do not study the impact of culturally influenced price setting on sale outcomes, we propose that the selection of the 8 price ending is motivated by the expectation that culturally attractive numbers in list prices have a positive relationship with buyer intensity and thus final sale prices. This gives our next hypotheses:

Hypothesis 5a: The use of 5 and 9 price endings results in higher *SLPD*, all else being equal.

Hypothesis 5b: The use of 8 price ending in *HC* areas results in lower *SLPD*, all else being equal.

The second sale outcome considered is selling time, measured as *ToM*. The marketing literature finds that just below price endings are associated with higher sales volume (Schindler and Kirby 1997). In real estate, this translates as higher buyer demand and is expected to decrease selling time. However, Beracha and Seiler (2015) and Palmon, Smith and Sopranzetti (2004) find that properties listed using just below pricing devices take longer to sell. Our final hypothesis seeks to address this conflict and extend it to also consider how culturally significant prices affect the relationship between *ToM* and list prices:

Hypothesis 6: The use of 5, 9 and, in *HC* areas, 8 price endings decrease the time to sale, all else being equal.

The results of this final hypothesis have implications for the broader ask price literature and the impact of list prices on sales turnover. While Schindler and Kirby (1997) document that retail sales are higher when just below pricing is used, psychology research, such as that of Vanheule, Laurent and Dreze (2006), show that unusual numbers are associated with better consumer recall. That is, when exposed to price endings that are less common, consumers are more likely to recall the price and product, which the authors predict to have a strong association with sales.

Methodology

Identifying price endings

A complicating factor in the analysis of list price endings for real estate is the typically large set of trailing zeros. That is, many sale prices are described in thousand-dollar (or even million-dollar) terms. To overcome this complicating factor, we adopt the approach of Simmons and Schindler (2003) and consider the first non-zero term from the right side of the price to be the price ending digit.[3] Zero is considered the price ending if the first non-zero term is also the left-most term of the price (e.g. $800,000). Our approach differs from that of previous real estate studies on list price endings, such as Beracha and Seiler (2014) and Palmon, Smith and Sopranzetti (2004). These earlier papers rely on the 'thousands digit' – the fourth price digit from the right. The treatment of trailing zeros used in our paper is supported by the consumer psychology literature that documents a stronger behavioral influence of a price's last non-zero digit than of other numbers, including the 'true' last digit (Bizer and Schindler 2005).

Measuring price ending frequencies

[3] To demonstrate, consider the following three prices and their price endings: (i) $910,000; 1; (ii) $1,732,000; 2; (iii) $1,833,333; 3.

Hypotheses 1, 2 and 3 refer to the frequency with which specific digits are represented as list price endings. Specifically, we aim to test whether certain numbers are more common than others, first within samples and then across subsamples. Hypothesis 1 is tested by using binomial tests to measure whether the distribution of price endings is consistent with a random chance expectation, for which we assume a uniform distribution (10 percent frequency for each digit) in the sample. Then, to test Hypotheses 2, 3a and 3b (whether there is a difference in relative frequencies between subsamples), *t*-statistics for differences in means at each price ending are calculated.

Hypothesis 3a specifically considers the differences in list price choices between sellers of low and high-priced properties. We define houses and apartments as low priced if the property is listed at a price below the trailing 12-month suburb median sale price observed for that property type.

Sale likelihood, price discounting and time on market

Hypotheses 4, 5a and 5b are concerned with the effect of price endings on the likelihood of a sale, *SLPD*, and *ToM*. Difference-in-means tests are performed first to detect any significant variations in these sale outcomes by price ending. However, a number of other factors must be controlled for since we are considering the impact of the choice of price ending on sale outcomes. The following discrete choice, regression and hazard models are developed to test each of the sale outcomes.

To determine whether price endings affect the likelihood of a sale, the following probit model is estimated by maximum likelihood:

$$Sale = f(End, ListPrice, OverPricing, Landsize, Location, Year) \qquad (1)$$

where the dependent variable, *Sale*, takes a value of 1 when a sale is recorded against the listing and 0 otherwise; *End* is a matrix of dummy variables for each list price ending that takes a value of 1 where the listing has the price ending under examination and 0 otherwise; *ListPrice* is the list price value; *Overpricing* is the difference between *ListPrice* and the median postcode sale price in the previous month; *Landsize* is the natural logarithm of the property's land size (house subsample only); and *Location* and *Year* are fixed effects defined as the property's postcode and year of sale, respectively.

A regression model is estimated to test the effects of price ending on *SLPD*. The regression model is specified as:

$$Discount = \alpha + \Sigma\beta_k.End_k + \gamma_1 ListPrice + \gamma_2 OverPricing + \gamma_3 TOM + \gamma_4 TOM^2 \qquad (2)$$

$$+\gamma_5 LandSize + Year + Location + \epsilon$$

where the dependent variable, *Discount*, is the *SLPD* measured as the percentage difference between the sale price and initial list price; *TOM* is measured as the number of days between the initial listing and sale; ε is the OLS error term; and all remaining variables are specified as in equation (1).

Finally, to test Hypothesis 6, we estimate a hazard function to model *ToM*. The operational model is given as:

$$TOM = \alpha + \Sigma\beta_k.End_k + \gamma_1 ListPrice + \gamma_2 OverPricing + \gamma_5 LandSize + Year + Location \quad (3)$$

with variables specified as in the previous equations. A Weibull hazard function is chosen to capture the heterogeneity in the likelihood of a sale as *TOM* increases. Our study has an advantage over earlier research in that we also have information on listings that did not sell. Thus, the estimated hazard model can better account for the right censoring that occurs when a sale does not occur.

Data and results

Data

Sales, listing and attribute data for all houses and apartments that were advertised for sale in Sydney during the period 1 January 1995 to 30 June 2014, as compiled by CoreLogic RP Data, are obtained from Sirca. The CoreLogic RP Data database effectively contains every property listing and transaction that publicly occurs, through a combination of Valuer-General and realtor feeds, web scraping and manual data input. The listing data include the start and end dates for the listing period as well as the initial list price. List price revisions are not available for this study. When the initial list price is reported with text indicating a price floor (for example, "Offers from $900,000"), we take the denoted price value. Similarly, when the initial list price is reported as a range (for example, "$850,000-$870,000"), we take the lower end. Our results are consistent when the upper price of a range is taken instead.

We restrict our sample to residential properties listed for sale by negotiation in the Sydney metropolitan region, as defined by the Statistical Division boundaries in the Australian Standard Geographical Classification. Properties with missing location and list price information are removed. Properties listed as for auction, mortgagee sale and like-exchange are also excluded. Filters are then applied to remove outliers, which are defined as prices beyond the 1st and 99th percentile for each property type by suburb and year.

Notably, our dataset includes listing information for properties that sell and those that do not, which is a substantial benefit over earlier studies. We match a listing to a sale outcome when the property sale occurs not earlier than 1 day after the start of the listing period and not later than 90 days after the end of the listing period.

Suburb demographic and immigration data are obtained from the 2011 Australian Census, which is accessible via the Australian Bureau of Statistics. We calculate the proportion of residents in each suburb that migrated to Sydney by their country of birth. Suburbs are defined as *HC* when the total proportion of their population from countries holding a preference for the number 8 exceeds 15 percent. The list of countries that we use to reflect this cultural preference include China (including the Special Administrative Regions of Hong Kong and Macau), Taiwan, Singapore, and Malaysia. This list is compiled by using the results of various studies on the so-called "lucky floor effect", which have attributed a documented price premium paid for apartments on the 8th floor to superstition.

Descriptive statistics of the sample dataset are presented in Table 1. The full sample, described in Panel A, comprises 269,459 listings of houses and 161,986 listings of apartments. Approximately 60 percent of the listings are matched to successful sales. The average sale price is lower than the average list price, indicating positive average seller discounting. That is, the realized sale price is less than the advertised list price on average across the sample. Both the average sale and list price are higher than their respective medians, indicating a high positive price skew. Further, high-priced properties take more time to sell than low-priced properties on average, though they are also associated with less *SLPD* than low-priced properties.

<Insert Table 1>

A key part in this study is to analyze listing behavior across populations of different cultural backgrounds. Panel B presents statistics from the subsample of listings in *HC* suburbs, as defined above. While approximately 10 percent of the sample listings are for properties located in *HC* suburbs, these suburbs have many more apartments than houses, explaining the skewed proportion in the *HC* sample towards apartments. Houses in *HC* suburbs are more expensive and list for higher prices, on average, while apartment prices are comparable between the *HC* subsample and full sample.

Price ending frequencies

Using the procedure outlined in Section 3.1, relevant price endings are identified for each listed property. Figure 1 presents the distribution of price endings across each digit from 0 through 9. Price ending clusters at 5 and 9 are apparent. Interestingly, for the *HC* subsample, there are spikes in the frequency of 8 as a price ending that are not apparent in the full sample.

<Insert Figure 1>

To formally test Hypothesis 1, we consider the results of a binomial test. Table 2 reports the relative frequencies of list prices at each price ending as percentages as well as the statistical significance of each price ending from a binomial test.

<Insert Table 2>

The first column of Table 2 shows that for both houses (Panel A) and apartments (Panel B), the 5 and 9 price ending are statistically significant and economically substantially more frequently used than other price endings. This result is consistent with the previous price ending literature and supports Hypothesis 1.

Zero as a price ending is the next most frequently used, followed by 8. A comparison of price endings for low- and high-priced properties in the next two columns shows an increase in clustering at 0 for the higher priced subsample and a decrease in the frequency of 9 as a price ending. This result is consistent with our expectation that just below pricing is less commonly used for higher priced properties.

The right-most columns of Table 2 present relative price ending frequencies for the subsample of listings in *HC* suburbs. The most common price endings again are 5 and 9.

However, 8 is now statistically significantly more common than otherwise expected. The pattern observed for the 0 and 9 price ending the between high- and low-priced samples is similarly repeated in the *HC* subsample. The use of 8 as a price ending appears to be relatively more consistent across differently priced properties.

To further examine differences between subsamples, formal difference-of-means statistical testing is used. These results are reported in Table 3. Panel A reports the difference in price ending proportions between *HC* suburbs and non-*HC* suburbs. Our results show statistically significantly higher use of 8 as a price ending in *HC* suburbs than other areas, which provides support for our second hypothesis. Price ending strategies are not universal; rather, they are chosen to target the prospective buyers' preferences and biases.

<Insert Table 3>

Panel B of Table 3 reports difference-in-means between the high and low-priced property subsamples for all suburbs and Panel C reports these statistics for the *HC* suburbs subsample. As noted earlier, the use of just below pricing is lower for higher priced properties. The final column of Table 3 shows a statistically significant decline in the use of 9 as a price ending for the high price subsample, supporting Hypothesis 3a. The first column in Panel B shows that across all properties, the decline in the use of 9 as a price ending is offset by statistically significantly increased use of 0.

The drop-off in the use of just below pricing is consistently detected in the *HC* subsample. There is weak evidence to suggest that the use of 8 as a price ending increases in higher priced properties; however, this is not uniformly observed across houses and apartments. Regarding Hypothesis 3b, the results are inconclusive, and we cannot reject the null that culturally relevant auspicious price endings are equally prevalent in high- and low-priced properties. This result indicates that price ending patterns for residential real estate and consumer goods follow different strategies for different value ranges.

Sale outcomes

The next set of results refers to the outcomes of the listing campaign. First, did the property sell? Then, if it sold, did the listing strategy (specifically, the choice of a particular price ending) beneficially affect the price (up) and *ToM* (down)?

Table 4 summarizes the average of these sale outcome variables and groups them by list price ending. The sale rate is the percentage of listings that result in a sale. *ToM* is the number of calendar days between and the start of the listing campaign and the sale date. *SLPD* is the discount from the initial list price to the sale price. The four separate panels present the results for the full sample and the *HC* subsample by property type.

<Insert Table 4>

First, considering the sale rate percentages in the top row does not appear to yield any consistent pattern regarding the price ending. Further, there is little economic variation in the means, indicating little real marginal effect from the price ending. To confirm whether the price ending has any impact on the sale rate, a probit model is estimated. However, in the interest of space, the full set of these results is not presented here.[4] There is weak statistical support indicating that the use of 9 as a price ending increases the sale rate for apartments, all else being equal. This result is not observed for houses. Furthermore, there is no statistical support to indicate that the 8 price ending affects the sale rate for either the full sample or the *HC* subsample. These results do not support the rejection of the null hypothesis that price endings have no impact on the likelihood of a sale.

The left-most column in Table 4 indicates that *SLPD*, on average, is positive across all listings, with the error being higher for houses (1.90 percent) than apartments (1.00 percent). We make several key observations from *SLPD* difference-in-means tests at each price ending. First, for price endings of 0, the average *SLPD* is negative and significant, with a range from about -3.1 percent to -4.0 percent. That is, listings ending in 0 typically sell at a higher price than their listing value, and this difference is significantly greater for such price endings than for other price endings. Next, we observe that the *SLPD* for properties listed at prices ending with 5 or 9 are positive and statistically significant. This result indicates that listings with these most common price endings sell for less, on average, than listings with price endings at other digits relative to their list price. Finally, we observe that statistically significant discounting from the list price occurs with 8 endings, and this discounting has the highest economic significance (2.45 percent for houses and 1.94 percent for apartments) in *HC* suburbs.

Taken at face value, the *SLPD* results just discussed bring into question why these price endings are chosen. Many other factors could influence the difference between the list and

[4] The table containing the probit results is available from the authors upon request.

sale price. Thus, to further analyze the *SLPD* results, we consider the results from estimating the regression model given by Equation 2. The regression results are presented in Table 5. To ensure full rank, the dummy variable for prices ending in 1 is omitted from the model in the estimates presented.

<Insert Table 5>

Controlling for other factors that may affect *SLPD*, our results are broadly consistent with the univariate analysis. That is, all else being equal, just below endings achieve higher price discounting from their list prices. The results for the *HC* subsample reveal that both just below and lucky 8 price endings lead to significant *SLPD*. Evidence is found to support the expectation that price endings affect sales prices – but not in the direction expected under Hypothesis 5b. In line with the results of earlier studies, such as Beracha and Seiler (2014), 5 and 9 lead to greater discounting. Contrary to our expectation under Hypothesis 5b, lucky 8 price endings also result in greater *SLPD*. There may exist a rational motivation for so many sellers to choose these price endings, however, if they lead to a decrease in selling time.

Contrasting with the predictions of real estate search theory, the regression estimates presented in Table 5 indicate that a positive relationship exists between *ToM* and *SLPD*. The positive coefficient on the *ToM* term and negative coefficient on the ToM^2 term indicate that *SLPD* increases at a decreasing rate the longer the property's listing period.

Table 6 presents a hazard model to study the factors that affect time to sale of listings. This examination allows us to determine whether specific price endings affect *ToM*. An advantage of our approach over earlier studies is that we include properties that are listed but fail to sell and thus avoid sample selection bias.

<Insert Table 6>

The hazard model results provide only limited support for Hypothesis 6. For apartments, a negative coefficient for 5 price endings indicates that list prices with this device sell in shorter times on average, all else equal. There is no evidence to indicate that the price ending 8 affects *ToM* in *HC* suburbs. Interestingly, relatively uncommon price endings such as 3 and 4, are most consistently observed to decrease selling times. As found in earlier literature, higher prices and higher overpricing are associated with longer average *ToM*.

Conclusion

In this paper, we analyze the relationship between property sale outcomes and list price strategy. This is the first paper to document clustering in property list prices that are culturally significant. The results show that list prices for residential real estate in Sydney cluster at round and just below price endings – 0, 5 and 9. Further, in areas with large migrant communities from Asian countries, there is also significant clustering at 8. In a number of Asian counties, the number 8 is culturally significant and associated with fortune. We argue that this listing strategy is undertaken by sellers seeking to achieve the greatest appeal to prospective buyers and positively affect sale outcomes.

However, culturally significant 8 endings are not found to achieve more optimal sale outcomes than alternative price endings. Rather, the evidence presented in this paper indicates that 0 ending and uncommon price endings achieve less discounting (better price outcomes), while uncommon endings also result in shorter *ToM*.

Price endings of 8 are associated with higher discounting but not less listing time. Clustering at culturally significant price endings indicates a seller bias that buyers are not reacting to in their purchase decision. A possible rational explanation for this behavior may be that sellers' agents are choosing these price ending to attract future sellers. Agent behavior is beyond the scope of this paper, and we suggest it as an area for future research.

In bridging the research gaps regarding culture, housing market participant behavior and marketing psychology, the findings of this paper point to further areas of application in finance and real estate. Though price endings in these disciplines are extensively studied, no earlier papers have considered price ending preferences in a multicultural market. An extension might consider whether culture affects offer prices in real estate negotiations and auctions. Similarly, research into securities market structures might consider if quotes, more so than sale prices (as studied in Brown and Mitchell 2008), reflect cultural biases.

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Tables

Table 1

Descriptive Statistics

Table 1 presents descriptive statistics for the main data sample used in this study. The statistics are presented separately for houses and apartments, as well as for the low price and high price subsamples within each property type. The number of observations of both listings and matched sales are reported. Both the mean and median sale price (where a listing has a matched sale) and list price are reported. The means of two sale outcome variables, *SLPD* and *ToM*, are also presented. *SLPD* is the percentage difference between the initial list price and sale price. *ToM* is the number of days between the initial listing and sale date. Panel A presents the results for the full sample, and Panel B presents the results for the subsample of properties in *HC* suburbs.

	Houses – All	Houses – Low Price	Houses – High Price	Apartments – All	Apartments – Low Price	Apartments – High Price
Panel A: Full sample						
Observations - Listings	269,459	135,672	133,787	161,986	81,388	80,598
Observations - Sales	160,183	83,386	76,797	94,188	47,838	46,350
Sale Price ($), mean	626,402	389,942	883,147	463,508	324,926	606,539
Sale Price ($), median	520,000	385,000	755,000	420,000	325,000	550,000
List Price ($), mean	669,835	397,822	945,681	479,479	325,522	634,945
List Price ($), median	545,000	395,000	780,000	425,000	329,950	550,000
SLPD (%), mean	2.38	3.01	1.54	1.68	2.30	1.10
ToM (days), mean	61.77	59.90	63.96	50.32	50.31	50.32
Panel B: HC suburbs						
Observations - Listings	11,866	1,979	9,887	26,477	12,158	14,319
Observations - Sales	6,941	1,048	5,893	15,428	7,242	8,186
Sale Price ($), mean	841,313	440,268	912,634	467,119	337,454	581,832
Sale Price ($), median	750,000	442,000	797,500	432,000	340,000	531,694
List Price ($), mean	883,610	442,076	971,989	485,675	339,188	610,054
List Price ($), median	759,000	450,000	820,000	440,000	349,000	549,000
SLPD (%), mean	1.24	2.32	0.99	1.42	1.56	1.19
ToM (days), mean	61.12	61.49	61.06	49.70	46.95	52.10

Table 2

Price Endings Relative Frequencies

Table 2 reports the relative frequencies of list prices at each price ending as percentages. Panel A contains the results for house listings, while Panel B contains the analogous results for apartment listings. Relative frequencies are calculated on the full sample and the *HC* subsample separately. The analysis is performed with further stratification into low price and high price subsamples. Statistical significance of the binomial test for each price ending (or combination of price endings) against a uniform distribution null is indicated at the 1%, 5%, and 10% levels by ***, **, and *, respectively.

	Full Sample			*HC* Suburbs		
	All	Low Price	High Price	All	Low Price	High Price
Panel A: Houses						
0	8.91	5.55	12.31***	13.94***	10.06	14.72***
1	2.73	2.27	3.19	3.63	3.18	3.72
2	4.22	3.52	4.93	5.21	4.24	5.40
3	3.18	2.71	3.66	4.25	2.93	4.51
4	2.78	2.64	2.91	2.81	2.53	2.87
5	40.57***	42.61***	38.5***	32.39***	31.73***	32.52***
6	2.64	2.47	2.81	2.87	2.63	2.92
7	2.76	2.68	2.84	2.83	2.63	2.87
8	5.16	4.08	6.26	12.39***	12.53***	12.36***
9	27.06***	31.47***	22.59***	19.68***	27.54***	18.10***
Panel B: Apartments						
0	8.88	6.04	11.75***	8.77	6.02	11.10***
1	2.53	2.31	2.75	2.24	2.02	2.44
2	4.28	4.04	4.52	4.34	4.28	4.40
3	3.42	3.07	3.76	3.81	3.45	4.11
4	2.80	2.65	2.95	2.44	2.43	2.44
5	38.77***	40.08***	37.45***	32.96***	33.96***	32.11***
6	2.86	2.79	2.94	2.96	2.80	3.09
7	2.98	2.89	3.08	2.96	3.00	2.92
8	6.86	6.36	7.37	11.68***	10.86***	12.38***
9	26.62***	29.77***	23.44***	27.84***	31.18***	24.99***

Table 3

Difference-in-Mean Price Ending Relative Frequency

Table 3 reports the difference-in-mean proportions of each price ending between different subsamples. To analyze the significance differences between the subsamples, *t*-statistics are reported in parentheses below each difference in mean. The results are presented for all properties, as well as houses and apartments, separately. Panel A reports the difference between *HC* suburbs and non-*HC* suburbs across all listings in the full sample. Panels B and C present the difference between high price and low price listings, for the full sample and the *HC* subsample, respectively.

	0	1	2	3	4	5	6	7	8	9
Panel A: HC – Non-HC, Full Sample										
All	1.62	0.03	0.40	0.740	-0.25	-7.81	0.23	0.08	6.69	-1.74
	(9.98)	(0.29)	(3.62)	(7.15)	(-2.96)	(-30.95)	(2.60)	(0.90)	(39.58)	(-7.46)
Houses	5.26	0.95	1.03	1.11	0.04	-8.56	0.25	0.08	7.56	-7.72
	(16.31)	(5.43)	(4.98)	(5.92)	(0.26)	(-19.44)	(1.59)	(0.48)	(24.75)	(-20.57)
Apartments	-0.13	-0.34	0.08	0.47	-0.43	-6.95	0.12	-0.03	5.76	1.45
	(-0.67)	(-3.35)	(0.55)	(3.67)	(-4.08)	(-21.84)	(1.04)	(-0.29)	(27.75)	(4.83)
Panel B: High Price – Low Price, Full Sample										
All	6.36	0.74	1.07	0.86	0.27	-3.56	0.27	0.17	1.75	-7.93
	(73.74)	(15.1)	(17.35)	(15.77)	(5.47)	(-23.86)	(5.43)	(3.35)	(24.53)	(-58.99)
Houses	6.76	0.92	1.42	0.95	0.26	-4.10	0.34	0.15	2.19	-8.89
	(61.87)	(14.65)	(18.3)	(14.06)	(4.17)	(-21.72)	(5.51)	(2.41)	(25.64)	(-52.21)
Apartments	5.71	0.44	0.48	0.69	0.29	-2.64	0.15	0.20	1.01	-6.33
	(40.55)	(5.62)	(4.75)	(7.67)	(3.56)	(-10.89)	(1.81)	(2.34)	(8.04)	(-28.92)
Panel C: High Price – Low Price, HC Sample										
All	5.99	0.78	0.54	0.90	0.17	-1.37	0.244	-0.05	1.28	-8.49
	(20.10)	(4.77)	(2.45)	(4.51)	(1.04)	(-2.75)	(1.38)	(-0.28)	(3.79)	(-18.03)
Houses	4.66	0.539	1.16	1.58	0.35	0.78	0.30	0.25	-0.17	-9.43
	(6.10)	(1.23)	(2.28)	(3.65)	(0.89)	(0.68)	(0.74)	(0.62)	(-0.21)	(-8.76)
Apartments	5.08	0.42	0.123	0.67	0.01	-1.85	0.29	-0.08	1.53	-6.19
	(14.96)	(2.33)	(0.49)	(2.85)	(0.05)	(-3.19)	(1.39)	(-0.40)	(3.87)	(-11.16)

Table 4

Price Endings and Sale Outcomes

Table 4 presents the means of three sale outcome variables. Sale rate is the percentage of listings that have a resulting sale, *SLPD* is the discount from the initial list price to sale price, and *ToM* is the number of days between the initial listing date and sale date. Sample means and the mean for each variable by list price ending are presented, with difference-in-means significance indicated at the 1%, 5%, and 10% levels by ***, **, and *, respectively. Panels A and B present the results for houses in the full sample and in the *HC* subsample, respectively. Panels C and D present the analogous results for apartments.

	All	0	1	2	3	4	5	6	7	8	9
Panel A: Houses, All											
Sale rate (%)	59.45	57.86***	58.97	59.10	60.66**	60.97***	59.90***	59.26	58.85	57.98***	59.45
SLPD (%), mean	1.90	-3.13***	0.30***	0.63***	0.19***	0.26***	2.57***	0.08***	0.33***	0.64***	3.82***
ToM (days), mean	61.71	60.72*	59.36**	60.90	58.45***	59.22***	61.50	58.42***	58.69***	60.88	64.15***
Panel B: Houses, HC											
Sale rate (%)	58.49	55.20***	58.93	60.52	57.94	58.98	59.35	56.89	56.85	58.30	59.44
SLPD (%), mean	1.24	-3.86***	-0.36***	0.68	-0.44**	-0.58***	1.55**	0.89	0.46*	2.45***	3.89***
ToM(days), mean	60.94	62.63	60.37	55.40*	53.04**	61.67	61.11	63.70	61.47	62.88	61.05
Panel C: Apartments, All											
Sale rate (%)	58.15	58.96**	56.07***	58.46	59.05	58.14	58.05	58.21	57.04	57.03**	58.44
SLPD (%), mean	1.00	-4.01***	0.59***	-0.32***	-0.60***	-0.85***	1.53***	0.83***	1.91***	0.36***	3.14***
ToM (days), mean	50.54	48.65***	51.08	48.68**	47.01***	47.83**	50.71	48.27**	47.56***	49.46	52.76***
Panel D: Apartments, HC											
Sale rate (%)	58.27	58.83	53.20**	58.09	59.13	57.12	57.60	56.38	58.75	57.55	59.76***
SLPD (%), mean	1.42	-3.82***	0.92	0.05***	-0.55***	-0.81***	1.79***	0.48***	1.44***	1.94***	3.62***
ToM (days), mean	50.06	50.16	44.46*	49.87	45.60**	44.31**	50.89	47.71	45.80*	50.41	51.12

Table 5

Regression – Sale-to-List-Price Discounting

Table 5 reports the OLS coefficient estimates from the regression model given by:

$$Discount = \alpha + \Sigma\beta_k . End_k + \gamma_1 ListPrice + \gamma_2 OverPricing + \gamma_3 TOM + \gamma_4 TOM^2 + \gamma_5 LandSize + Year + Location + e$$

where the dependent variable, *Discount*, is the percentage difference between the sale price and initial list price; *End* is a matrix of dummy variables for the list price end; *ListPrice* is the list price value; *Overpricing* is the difference between *ListPrice* and the median postcode sale price in the previous month; *Landsize* is the natural logarithm of the property's land size (house subsample estimation only); and *Location* and *Year* are fixed effects defined as the property's postcode and year of sale, respectively. The columns from left to right represent the model estimated over the following samples: houses in the full sample, houses in the *HC* subsample, apartments in the full sample, and apartments in the *HC* subsample. Below, *t*-statistics for each estimate are reported in parentheses. Statistical significance of the estimate is indicated at the 1%, 5%, and 10% levels by ***, **, and *, respectively.

Variable	Houses - All	Houses - *HC*	Apartments - All	Apartments - *HC*
Intercept	-2.53	2.18	-5.76***	-5.40***
	(-0.68)	(0.47)	(-21.96)	(-9.05)
0	-3.17***	-3.15***	-3.81***	-4.18***
	(-33.91)	(-7.09)	(-31.75)	(-13.13)
2	0.23**	1.10**	-0.58***	-0.66**
	(2.18)	(2.16)	(-4.34)	(-1.91)
3	-0.05	0.76	-0.69***	-1.05***
	(-0.46)	(1.43)	(-4.97)	(-2.98)
4	-0.09	-0.46	-0.90***	-1.28***
	(-0.75)	(-0.78)	(-6.21)	(-3.28)
5	1.64***	1.47***	0.76***	0.55*
	(19.46)	(3.57)	(6.91)	(1.86)
6	-0.22*	0.96	-1.03***	-1.16***
	(-1.87)	(1.62)	(-7.15)	(-3.07)
7	-0.05	0.43	-1.10***	-2.13***
	(-0.42)	(0.71)	(-7.64)	(-5.72)
8	0.18*	2.09***	-0.13***	0.75**
	(1.81)	(4.67)	(-1.08)	(2.40)
9	2.68***	3.64***	2.15***	2.24***
	(31.07)	(8.43)	(19.25)	(7.51)
ListPrice	0.38***	0.89**	2.32***	2.50***
	(3.49)	(1.66)	(9.65)	(3.87)
OverPricing	1.59***	1.54***	0.36***	0.49
	(21.53)	(3.28)	(3.27)	(1.64)
TOM	0.06***	0.07***	0.07***	0.062***
	(110.26)	(20.78)	(84.56)	(33.25)
TOM^2	-0.00***	-0.00***	-0.00***	-0.00***
	(-66.47)	(-13.57)	(-54.69)	(-22.29)
LandSize	-0.45***	-1.19***		
	(-16.69)	(-6.04)		
Year FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes
Observations	153,419	6,435	90,989	14,959
Adjusted R^2	0.3479	0.3050	0.3302	0.3061

Table 6

Hazard Model - Time on Market

Table 6 reports the estimated coefficients from fitting the following hazard model assuming a Weibull distribution:

$$TOM = \alpha + \Sigma\beta_k . End_k + \gamma_1 ListPrice + \gamma_2 OverPricing + \gamma_5 LandSize + Year + Location$$

where the dependent variable, *ToM*, is the number of days between the initial listing date and sale date; *End* is a matrix of dummy variables for the list price end; *ListPrice* is the the list price (scaled by $1,000,000); *Overpricing* is the difference between *ListPrice* and the median postcode sale price in the previous month; *Landsize* is the natural logarithm of the property's land size (house subsample estimation only); and *Location* and *Year* fixed effects are defined as the property's postcode and year of sale, respectively. The columns from left to right represent the model estimated over the following samples: houses in the full sample, houses in the *HC* subsample, apartments in the full sample, and apartments in the *HC* subsample. Below, χ^2 statistics for each coefficient estimate are reported in parentheses. Statistical significance of the estimate is indicated at the 1%, 5%, and 10% levels by ***, **, and *, respectively.

Variable	Houses - All	Houses - *HC*	Apartments - All	Apartments - *HC*
Intercept	4.64***	4.81***	5.91***	6.38***
	(13.60)	(13.26)	(3385.48)	(696.16)
0	0.15***	0.33**	-0.04	-13.04
	(22.68)	(6.11)	(0.56)	(1.07)
2	0.02	-0.07	-0.11**	-15.07
	(0.20)	(0.24)	(4.26)	(1.20)
3	-0.08**	-0.02	-0.11**	-24.29*
	(4.30)	(0.01)	(4.30)	(3.02)
4	-0.08**	-0.11	0.04	-0.07
	(4.69)	(0.43)	(0.62)	(0.18)
5	-0.01	0.00	-0.10**	-0.13
	(0.25)	(0.00)	(5.01)	(1.20)
6	-0.03	-0.12	-0.03	-0.02
	(0.88)	(0.47)	(0.30)	(0.02)
7	0.00	0.18	0.00	-0.16
	(0.01)	(0.96)	(0.01)	(1.19)
8	0.08**	0.06	0.01	-0.12
	(5.09)	(0.22)	(0.07)	(0.93)
9	0.03	0.08	-0.09**	-0.18
	(0.75)	(0.36)	(4.12)	(2.41)
ListPrice	0.34***	0.79***	0.67***	0.49*
	(91.37)	(27.99)	(50.79)	(3.31)
OverPricing	0.70***	0.07	0.40***	0.36***
	(831.62)	(0.32)	(84.67)	(8.40)
LandSize	0.08***	0.01		
	(82.75)	(0.08)		
Year FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes
Observations	253,742	10,804	154,921	25,615
Log-likelihood	863,928	36,692	536,906	88,875

Figures

Figure 1

List Price Endings

Figure 1 charts the percentage frequency of each price ending by property type for the full sample and for the *HC* suburb subsample. The bars represent (from top to bottom): apartments in the *HC* subsample, apartments in the full sample, houses in *HC* subsample, and houses in full sample. The percentage is also presented at the right end of each bar. The vertical red line displays the expected frequency under a uniform distribution.