The Cost of a Lucky Price

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ABSTRACT

Real estate buyers pay a premium for lucky properties. Using a large sample of Hong Kong apartment sales, we show that the transaction price itself is priced as a property attribute when it ends in a lucky 8 digit. This explains our observation of price clustering. Hedonic regression modelling is used to show that properties which sell at a lucky price also sell for a 1.4 percent premium, on average. Unlike lucky floor premium, lucky price premium does not exhibit luxury goods characteristics and is not sensitive property price cycles. This shows that the lucky price premium is attributed to cultural heuristics. The results are robust to alternative model specifications.

Keywords: House prices, superstition, price endings, behavioral economics

JEL Classification: C78, G02, M37, R23, R30

1. Introduction

In a diverse range of investments and goods, those considered lucky are found to attract a price premium. In many cases, luck is defined by a numerical attribute, such as the floor number of an apartment or the digits in a telephone number. In this paper, we examine an additional channel where luck can affect behavior and prices: the actual numbers contained in a price.

The impact of luck and cultural heuristics on markets is a growing area of behavioral economics. The most salient of these heuristics is the 'lucky 8' preference in Chinese culture.

Several papers identify a price premium for lucky properties, where luck is identified by a number 8 in the property's location, such as the floor level or street number (Chau et al, 2001; Shum et al, 2014; Bourassa and Peng, 1999; Fortin et al, 2014). While a preference for prices ending in 8 is identified in Asian stock market trades (Brown and Mitchell, 2008; Brown et al, 2002) and consumer goods market price setting (Simmons and Schindler, 2003), no previous papers have considered whether a similar preference exists in real estate markets.

Our aims in this paper are twofold. We firstly seek to address this research gap by determining whether a cultural preference for 8 leads to clustering of sales at particular prices in real estate. Secondly, we analyze whether buyers incur an additional cost to achieve a lucky transaction price. In undertaking this second line of inquiry we offer a novel contribution to the broader behavioral economics literature in how the utility of superstition may be valued.

Using a comprehensive database of all residential property transactions for a large, private development in Hong Kong between June 1991 and August 2016, we find evidence of significant transaction price clustering at prices ending in $8,000. Furthermore, our results indicate that these transactions attract a 1.4 percent price premium, all else equal. That is, buyers incur an additional cost of 1.4 percent to achieve a lucky price. These results are robust to the housing market cycle as well as alternative markers of superstition. In a set of robustness checks, we find no evidence in support of a corresponding price discount for unlucky prices, nor interaction effect with a lucky floor. While properties on lucky floors are found to sell for more, supporting Chau et al (2001) this result appears to be independent of the lucky price effect.

The remainder of our paper is structured as follows. Section 2 provides a review of the price clustering and superstitious pricing literatures, from which we develop testable hypotheses. Sections 3 and 4 present the paper's research design and data, respectively. Section 5 reports and discusses our primary results. A set of robustness checks are presented in Section 6 and in Section 7 we conclude.

2. Literature Review and Hypothesis Development

A broad area of research considers the ways in which numbers affect behavior. In this section, we focus our review on the key literature in two areas: (i) price clustering, and (ii) the effect of lucky numbers on prices.

Researchers have identified price clustering as a way in which the effect of numbers on behavior may be observed. Price clustering occurs when transactions at particular numbers are more frequent than at other numbers.

Round number price clustering – that is, more frequent transactions at prices ending in 0 and 5 – is

widely observed in U.S. financial and housing markets. As a result of the modern decimal system, the tendency for trades to take place at round numbers is attributed to the relative mental ease of computing these numbers, a bias referred to as cognitive accessibility in the behavioral economics literature (Mitchell, 2001).

Aitken et al (1996) report significant clustering at prices ending in zero for individual stock trades on the ASX. The next highest degree of clustering is observed at prices that end in 5. Similar observations are made in the markets for derivatives (Gwylim et al, 1998), gold (Ball et al, 1985) and foreign exchange (Sopranzetti and Datar, 2002). This preference for round numbers extends to alternative representations of price. For example, Harris (1991) shows that prior to NYSE decimalization, stock market trades clustered at round fractions.

Shiller (2000) adds to the reasoning for the round number preference, noting that rounded numbers are useful proxies for fundamental values when uncertainty is high. This is particularly relevant in real estate markets, since low liquidity and high information asymmetries make fundamental values difficult to obtain.

In a sample of 6,385 residential property transactions from Houston, Texas, Palmon et al (2004) observe the price of 50 percent end in '-000'. The preference for round number price endings in real estate transactions is supported by Allen and Dare (2006) and Salter et al (2007). A secondary price clustering at prices ending in 9 is observed in the real estate literature. The 9 price ending is referred to alternatively in the real estate literature as just-below pricing, off-dollar pricing and charm pricing. These papers investigate the relationship between round number and just below price clusters and transaction outcomes, although there is little consensus.

To understand why 9 is a common price ending in real estate, it is firstly important to note that not all numbers in a price are worth the same amount, as the position of numbers in a price indicates a different economic significance. In standard Western representation of prices, the value increases by a factor of 10 at each consecutive leftward position, all else equal. The right-most position digits, which we refer to as price-endings, thus have the smallest economic value of a price.

Despite this, price endings are found to have a disproportionately high impact on economic outcomes in consumer behavior and financial markets. Ironically, this is because individuals tend to "drop off" price endings. Bizer and Schindler (2005, p.772) show in experimental marketing research that "consumers ignore, or give very little attention to, the ending digits of a price". In other words, because of their relatively low value, the weighting of price-endings is too low relative to more leftward numbers in economic decision making. Vendors optimize their own economic returns by taking advantage of this bias and setting price endings to 9.

Twedt (1965) is among the earliest paper to analyze the use of 9 endings by vendors in consumer goods, a phenomenon which is widely observed in the consumer research literature. Motivated by cultural economics, Simmons and Schindler (2003) extend the intuition behind the 9 ending to test for evidence of a 'lucky 8' ending in consumer goods. Using advertised prices for consumer goods in Shanghai, Hong Kong and Taiwan, Simmons and Schindler (2003) identify the most common price ending to be 8.

The number 8 is considered extremely lucky in China and among people of Chinese heritage living in other countries. This is because the Cantonese word for '8' sounds similar to that for 'prosperity (Chau, 2001). Over time, this relationship has evolved into a deep cultural belief that 8 is equivalent to good luck.

Extending the stock market research of Aitken et al (1996) and others, Brown and Mitchell (2008) identify evidence of clustering at stock prices which end in 8 on the Shanghai and Shenzhen stock exchange. This builds on work by Brown, Chua and Mitchell (2002) who represent the first examination of price clustering around cultural effects using data for several Asian markets. Brown et al's (2002) paper identifies a lucky 8 price clustering effect in China, but not in Australia, Indonesia, Philippines, Singapore or Taiwan where round-number clustering prevails. The price clustering in Hong Kong is strengthened at inauspicious dates, such as Chinese New Year.

No prior research in real estate markets has tested for a lucky number effect on price clustering. This presents an opportunity in the present study to consider an alternative approach to detecting superstitious behavior in real estate markets. To determine whether real estate prices cluster at lucky numbers and the impact of this behavior, it is important to note the different price scales between stocks and real estate. The average Hong Kong apartment prices is over $4 million. Unlike stock market clustering studies, where minimum trade increments are in cents, real estate prices in Hong Kong are commonly quoted in thousand-dollar terms. That is, the minimum price increment is typically $1,000. Furthermore, real estate prices in Hong Kong tend to be rounded to the nearest ten-thousand dollar unit, or "Wan" ("萬"), a special name for ten thousand in Chinese. For these reasons, we assume that superstitious pricing behavior will be observed in non-zero thousand-dollar digits. This leads to our first hypothesis:

Hypothesis 1: Real estate prices ending in 8 are more common that other non-zero real estate price endings

Our subsequent interest in this paper is determining if lucky numbers in transaction prices themselves influence prices. In other words, do buyers pay more in order to achieve a lucky price? If so, the transaction price itself may be an additional attribute of the property, particularly if it is a way of attracting additional status or prestige to the buyer. A number of papers identify a price premium for properties with similarly intangible lucky features.

Chau et al (2001) test whether lucky attributes are capitalized into prices in the real estate market. Specifically, the authors model the lucky 8th floor as an additional attribute in a hedonic pricing model. Using apartment sales data from Hong Kong, their results show that apartments on the 8th floor sell for 2.8% more than other apartments, all else equal.

Support for the 'luck' premium is found in similar studies of real estate address numbers in mainland China (Shum et al, 2014), Auckland, New Zealand (Bourassa and Peng, 1999), Singapore (Agarwal et al, 2016) and Vancouver, Canada (Fortin et al, 2014).

If the property price itself can be a potential attribute, it should be included in a pricing model alongside other features of the property. Thus, our second hypothesis aims to test whether lucky prices are considered an attribute:

Hypothesis 2: Transactions at lucky prices sell for a higher price than transactions at other prices, all else equal

Taken together, these hypotheses allow us to test whether there is superstition-driven clustering in property prices, and if so, how much are buyers prepared to pay in order to secure a lucky price. The following section sets out our paper's methodological approach to determine if there is empirical support for our hypotheses.

3. Research Design

To test our hypotheses, we first define price endings and lucky prices. Since property prices are large numbers, typically ranging from millions to tens of millions in Hong Kong, market convention is to quote prices in million-dollar terms to the third decimal place. As such, we consider the price ending to be the thousand-digit of a price as this is the standard minimum price increment. Use of the price thousand-digit is in line with previous US-based house price endings research (Palmon et al, 2004; Allen and Dare, 2004; Salter et al, 2007). Lucky prices are defined as those sales prices with 8 as the price ending digit.

Hypothesis 1 is concerned with the relative frequency of lucky prices. A higher proportion of sales at a lucky price indicates superstition-driven price clustering. To test whether superstition affects property market behavior in this way, we use a chi-square test for categorical data to examine whether the lucky price occurs more frequently than other price endings. Due to expected rounding of transaction prices to the nearest *Wan* (ten-thousand dollars), we exclude zero price endings and focus this test on non-zero price endings. A positive and significant test statistic would support our hypothesis and lead us to conclude that superstition leads to price clustering in the Hong Kong housing market.

Our next hypothesis tests the effect of lucky prices on the transaction prices itself. We utilize hedonic regression to test whether properties that transact at the lucky price attract a premium. Hedonic regression is a technique often used in house price analysis to estimate the implicit value of a property's attributes. Similar to other desirable property attributes, such as size and sea views, we treat lucky price as a variable that explains transaction price.

To test Hypothesis 2 we perform least-squares estimation of the following equation:

$$\log(NP) = \alpha + \beta_1 LuckyP + \beta_2 LuckyF + \beta_3 SFA + \beta_4 SFA^2 + \beta_5 AGE + \beta_6 AGE^2 + \beta_7 FL + \beta_8 FL^2 + \beta_9 SV + \beta_{10} TF + \sum \gamma_k TimeDummy_k + \epsilon \quad (1)$$

where our dependent variable, log(*NP*), is the natural logarithm of the nominal transaction price, and our primary explanatory variable, *LuckyP*, is a dummy variable equal to 1 if the transaction price is lucky (that is, 8 is the thousand dollar digit) and zero otherwise. A positive and significant coefficient on the lucky price dummy variable, *LuckyP*, indicates that transactions at lucky prices sell for a higher price, all else equal. This results would support our second hypothesis.

Equation 1 contains a number of additional control variables to capture the effect of other attributes on price. Specifically, *LuckyF* is a dummy variable equal to 1 if the last digit of the floor level number is 8 and zero otherwise, *SFA* is the saleable floor area, *AGE* is the property age at the transaction date, *FL* is the floor level, *SV* is a dummy variable equal to 1 if the apartment has a sea-view and zero

otherwise, *TF* is a dummy variable equal to 1 if for top-floor apartments (which includes roof) and zero otherwise, and *TimeDummy* is a dummy variable that equals 1 if the apartment is transacted at a particular month and year and zero otherwise.

Measures of property size, age, floor level and sea view are found in many real estate hedonic regression models to be significant determinants of price (see, for example, Chau (2001)). With the exception of age, we expect these hedonic variables to have positive estimated coefficients. To capture potential non-linear effects, we include square terms for *SFA*, *AGE* and *FL*. We expect to find negative coefficients for the squared terms of *SFA* and *FL*. Considered jointly with the linear term, this result indicates that the implicit value for size and floor levels increases, but at a decreasing rate. Conversely, we expect the estimated coefficient of the square of *AGE* will be positive. This implies non-linear decreases in price as a property becomes older, with newer properties experiencing larger proportional falls in value.

4. Data and Summary Statistics

Our empirical results utilize a rich dataset of transactions and property attributes from a single, private housing estate in Hong Kong. The estate, Taikoo Shing, is located on Hong Kong Island (see Figure 1) and represents one of the city's largest housing estates, built in nine phases between 1976 and 1987, and comprising a total development size of 12,308 apartments.

[Insert Figure 1]

An advantage of focusing our study on a single housing estate is to cancel out other uncontrolled variables. All Taikoo Shing apartments are comparable, with all towers being 30 stories high and built to similar internal specifications. This is benefits our research design, in which we aim to control for differences between apartments in order to isolate the lucky price effect through hedonic regression analysis.

Our sample range covers all property transactions in Taikoo Shing from June 1991 to August 2016. The data is obtained from EPRC, one of Hong Kong's largest and most widely used sources for property-related information. The EPRC database primarily records property transactions which are registered with the Hong Kong Government Lands Registry Office. Property and transaction details, are captured by EPRC and made available for this study. The information includes the transaction price and date, saleable floor area, floor level, age, aspect, and address. Summary statistics are shown in Table 1.

[Insert Table 1]

In total, we have 22,519 transactions in our sample. Despite Taikoo Shing now being considered a relatively old housing estate by Hong Kong standards, there is still considerable trading activity in its apartments. In our sample there are approximately 900 transactions per year on average.

Table 2 summarizes the frequency of price endings in our sample. We find that the market convention to round transaction prices to the nearest *Wan* resulting in a zero price ending, occurs in a high proportion of transactions (89.3 percent). Of the non-zero price endings, lucky prices are the most common. Prices ending in 8 account for 56.3 percent of non-zero price endings. This is a marked difference from price endings studies based in the US, where 5 and 9 are identified as the most common non-zero price endings (Palmon et al, 2004; Allen and Dare, 2006; Salter et al, 2007). In our sample, prices ending in 5 account for 27.8 of non-zero price endings, making it approximately half as popular as the lucky price.

Interestingly, the least frequently used price endings are 4 and 7. The number 4 is considered unlucky in Chinese culture, in part because it is similar in pronunciation for the Cantonese word for 'death'. Unlucky prices, those prices which end in $4,000 account for only 1 percent of the non-zero price endings in our sample.

[Insert Table 2]

The frequency counts presented in Table 2 support this paper's first hypothesis, that there is superstitious price clustering in the Hong Kong property market. We explore this effect statistically and seek to identify and quantify the impact of this effect on transaction prices in the next section.

5. Results and Discussion

5.1 *Price ending frequencies*

To determine if there is a statistically significant higher use of lucky prices than other non-zero price endings, we present a cluster analysis in Table 3. This table presents the distribution of 8 and non-8 thousand digits for the non-zero price ending sample, as well as the observed and expected frequencies of these two clusters.

[Insert Table 3]

It is shown that 8 price ending has the highest frequency (56.3 percent), while the remaining is non-8 price endings (43.7 percent). The chi-square test ($\chi^2 > 4{,}400$[df=1], $p < 0.001$) shows that lucky prices occur significantly more than chance would suggest. This result rejects the null hypothesis that lucky prices and other non-zero price endings are equally likely. Rather, this result supports our expectation that there is clustering in Hong Kong property prices that is motivated by superstition. This implies that buyers and sellers deliberately use 8 in thousand dollar digit in the transaction prices. We next test whether this preference comes at a price.

5.2 *Lucky numbers in transaction prices*

Table 4 presents the result of least-squares estimation of Equation (1). The estimated coefficient on transactions with lucky prices, *LuckyP*, is 0.014 and statistically significant at the 1 percent level. This provides strong evidence in support of our second hypothesis. That is, buyers in Hong Kong pay a

premium to achieve a lucky sale price, all else equal. Our results indicate that this premium is equal to 1.4% of the average transaction price. Using the average price reported in our descriptive statistics, this is approximately equivalent to HKD$65,800 (USD$8,500).

[Insert Table 4]

We also find a positive and significant coefficient on *LuckyF*, indicating that buyers are willing to pay a 1.9 percent premium for properties located on lucky floor. This finding suggests that lucky floor numbers are a property attribute that pricing models should incorporate, and is similar to the 2 percent lucky floor premium estimated in Chau et al (2001).

The estimated coefficients of the remaining regression variables are highly significant and have the *a priori* expected signs. Larger apartments, apartments on higher floors, and sea view and top-floor apartments all sell for higher prices, while older properties sell for less, on average. Our non-linear expectations for size, floor level and age are also in line with expectations.

5.3 *Robustness tests*

We check the robustness of our results in two ways. Firstly, we consider whether unluckiness has an inverse impact on behavior in the housing market, and secondly, whether our results are affected by the property market cycle. The results and discussion of these robustness tests are presented below.

i. Unlucky numbers

As a robustness test, we adapt Equation 1 to explore whether there is an inverse finding for unlucky prices and floor numbers. That is, for prices which contain 4 in the thousand-dollar digit. We have already identified that this is the most infrequently used price ending. To test the effect of unlucky numbers, we estimate the hedonic regression model given by Equation 2 which includes dummy variables for unlucky prices and unlucky floors:

$$\log(NP) = \alpha + \beta_1 LuckyP + \beta_2 UnluckyP + \beta_3 LuckyF + \beta_4 UnluckyF + \beta_5 SFA + \beta_6 SFA^2 + \beta_7 AGE + \beta_8 AGE^2 + \beta_9 FL + \beta_{10} FL^2 + \beta_{11} SV + \beta_{12} TF + \sum \gamma_k TimeDummy_k + \epsilon \quad (2)$$

where *UnluckyP* equals 1 if the transaction price ending is 4, and thus considered an unlucky price and zero otherwise and *UnluckyF* equals 1 if the last digit of the floor level number is 4 and zero otherwise.

Table 5 presents the estimated coefficients of Equation 2. We find that a negative association between transaction prices and unlucky prices. We interpret this finding as evidence of rational seller behavior. If there is a possibility that buyers will demand a discount for prices that in $4,000, they will rationally ask a higher price. This rational behavior explains the under-representation of the unlucky price ending. In line with earlier research (Chau et al, 2001), we also document a negative, but not

significant, estimated coefficient for properties on unlucky floors.

[Insert Table 5]

ii. Property market cycles

In this sub-section, we outline a method to detect booms and busts in the property market to assess whether the lucky price effect we have identified is affected by market cycles.

We adopt a statistical method to detect property market booms and busts, which measures the deviation of a price index from the smoothed long term trend. This is similar to the approach used in a range of asset markets, such as in credit boom detection (Mendoza and Terrones, 2008), boom/bust cycles of asset price (Alessi and Detken, 2011), and boom/bust cycles of housing price (Borgy et al., 2010). Other smoothing methods to identify the term trend have also been used in Christiano and Fitzgerald (2003).

This differs from the fundamental method, as used in earlier Hong Kong property market cycle research by Chau et al (2001). The reason the statistical method is chosen because prices in the Hong Kong housing market have continually increased since 2003, obscuring the underlying market cycle.

Monthly Hong Kong residential property price indices are obtained from the Rating and Valuation Department of the Hong Kong Government for the period January 1993 to November 2016. Figure 2 charts the Hong Kong private residential property price index.

[Insert Figure 2]

It is observed that the residential price index has steadily increased since a low-point in 2003. The resulting index is relatively smooth. To account for this, the Hodrick-Prescott (henceforth, 'HP') Filter is used to identify the boom and bust periods (Hodrick and Prescott, 1997).

Figure 3 shows the boom-bust periods for the Hong Kong private residential property index using the HP Filter. The log index and trend values are plotted on the right-hand axis while the left-hand axis plots the deviations. Deviations, *D*, are defined as the difference between the observed price index and the smoothed trend and are used to identify boom and bust periods. The observed price index is obtained from the HKU-Hong Kong Island Residential Price Index (HKU-HRPI).

[Insert Figure 3]

It could be argued that in boom markets, property buyers behave less rationally and a stronger lucky price effect may be identified. Conversely, it could be argued that a weaker lucky price effect may hold in bust periods when the buyers devalue this temporary attribute. To test the effect of property cycle on the lucky price effect, the interaction terms *UP* and *DN* are added to the hedonic regression model, as given by Equation 3:

$$\log(NP) = \alpha + \beta_1 LuckyP + \beta_2 LuckyP * UP + \beta_3 LuckyP * DN + \beta_4 UnluckyP + \beta_5 LuckyF + \beta_6 LuckyF * UP + \beta_7 LuckyF * DN + \beta_8 UnluckyF + \beta_9 SFA + \beta_{10} SFA^2 + \beta_{11} AGE + \beta_{12} AGE^2 + \beta_{13} FL + \beta_{14} FL^2 + \beta_{15} SV + \beta_{16} TF + \sum \gamma_k TimeDummy_k + \epsilon \quad (3)$$

where *UP* equals 1 if $D > 2\sigma_D$ and zero otherwise, and *DN* equals 1 if $D < -2\sigma_D$ and zero otherwise, given σ_D represents the standard deviation of *D*.[1] The parameters are estimated by ordinary least square with White's heteroscedasticity-corrected standard errors.

Table 6 reports the results of estimating Equation (3). The primary variable of interest, *LuckyP*, is significant at the 1 percent level, but there is no evidence to support a market cycle interaction effect. No interaction terms are found to be significant. This suggests that both boom and bust periods do not affect buyer preferences for lucky prices.

[Insert Table 6]

The value of a lucky floor also remains positive and significant. Further, the interaction term of floor is also positive and significant at the 1 percent level during the boom periods, but insignificant during the bust periods. Compared with lucky prices, which are not as visible and therefore less important status markers, apartments on lucky floors derive similar utility to luxury goods consumption. This result is consistent with Chau et al (2001), who describe this behavior as the "show-off" effect.

6. Conclusion

Lucky numbers are a major driver of housing market behavior. In this paper we present strong evidence of a previously undocumented channel through which this type of superstition affects housing markets - the transaction price itself.

Lucky prices, those which end in $8,000, are identified as the most common non-zero price ending using a large sample of transactions for a private Hong Kong housing estate. These lucky prices account for more than 50 percent of non-zero price endings. This is a major departure from the US housing market price ending literature, such as Palmon et al (2004), but consistent with the pattern of price endings for consumer goods marketed in China as reported by Simmons and Schindler (2003). It is also in line with the results of Asian stock market price clustering research (Brown et al, 2002; Brown and Mitchell, 2010), demonstrating a consistent pattern of superstitious behavior across different asset classes.

Furthermore, we develop a method by which we are able to measure the cost buyers pay in order to achieve a luck price. Using hedonic regression analysis which allows us to hold constant all other price-sensitive variables, we estimate buyers pay a 1.4 percent premium for lucky prices, on average.

[1] We also estimate Equation 3 using a lower threshold of one standard deviation for boom and bust definitions, and obtain similar results. For brevity we do not include here, but are available upon request from the author.

That is, given an average property price of HKD$4.7 million, lucky price cost around HKD$65,800 (USD$8,500). In other words, buyers are not only clustering at lucky prices, they are in fact prepared to pay more for a lucky price. Our results provide support for earlier evidence of a lucky-floor effect (Chau et al, 2001), and are robust to alternative superstitions and property market cycles.

References

Aitken, M., P. Brown, C. Buckland, H. Y. Izan and T. Walter, 1996, Price Clustering on the Australian Stock Exchange, *Pacific-Basin Finance Journal* 4(2), 297-314.

Alessi, L. and C. Detken, 2011, Quasi Real Time Early Warning Indicators for Costly Asset Price Boom/Bust Cycles: A Role for Global Liquidity, *European Journal of Political Economy* 27(3), 520-533.

Allen, M.T. and W.H. Dare, 2004, The Effects of Charm Listing Prices on House Transaction Prices, *Real Estate Economics* 32(4), 695-713.

Agarwal, S., J. He, H. Liu, I.P.L. Png, T.F. Sing and W. Wong, 2016. Superstition, Conspicuous Spending, and Housing Markets: Evidence from Singapore, Available at SSRN: https://ssrn.com/abstract=2416832.

Ball, C.A., W.A. Torous and A.E. Tschoegl, 1985, The Degree of Price Resolution: The Case of The Gold Market, *Journal of Future Markets* 5(1), 29-43.

Bizer, G. Y. and R. M. Schindler, 2005, Direct Evidence of Ending-Digit Drop-Off in Price Information Processing, *Psychology and Marketing* 22(10), 771-783.

Borgy, V., L. Clerc and J.P. Renne, 2010, 'House Price Boom/Bust Cycles: Identification Issues and Macro-Prudential Implications', *Housing Markets in Europe*, Springer Berlin Heidelberg, 359-383.

Bourassa, S. C. and V.S. Peng, 1999, Hedonic Prices and House Numbers: The Influence of Feng Shui, *International Real Estate Review* 2(1), 79-94.

Brown, P., A. Chua and J. Mitchell, 2002, The Influence of Cultural Factors on Price Clustering: Evidence from Asia-Pacific Stock Markets, *Pacific-Basin Finance Journal* 10(3), 307-332.

Brown, P. and J. Mitchell, 2008, Culture and Stock Price Clustering: Evidence from the Peoples' Republic of China. *Pacific-Basin Finance Journal* 16: 95-120.

Chau, K., V. Ma and D. Ho, 2001, The Pricing of 'Luckiness' in the Apartment Market, *Journal of Real Estate Literature* 9(1), 29-40.

Christiano, L. J. and T. J. Fitzgerald, 2003, The Band Pass Filter, *International Economic Review* 44(2), 435-465.

Fortin, N. M., A. J. Hill and J. Huang, 2014, Superstition in the Housing Market, *Economic Inquiry* 52(3), 974-993.

Gwilym, A. P., A.C. Owain and S. Thomas, 1998, Price Clustering and Bid-Ask Spreads in International Bond Futures, *Journal of International Financial Markets, Institutions and Money* 8(3), 377-391.

Harris, L., 1991, Stock Price Clustering and Discreteness, *Review of Financial Studies*, 4(3), 389-415.

Hodrick, R. and E. C. Prescott, 1997, Postward U.S. Business Cycles: An Empirical Investigation, *Journal of Money, Credit, and Banking* 29(1), 1-16.

Mendoza, E. G. and M. E. Terrones, 2008, An Anatomy of Credit Booms: Evidence from Macro Aggregates and Micro Data, National Bureau of Economic Research, working paper No. w140049.

Mitchell, J., 2001, Clustering and Psychological Barriers: The Importance of Numbers, *Journal of Futures Markets* 21(5), 395-428.

Palmon, O., B. Smith and B. Sopranzetti, 2004, Clustering in Real Estate Prices: Determinants and Consequences, *Journal of Real Estate Research* 26(2), 115-136.

Salter, S., K. Johnson and P. Spurlin, 2007, Off-Dollar Pricing, Residential Property Prices, and Marketing Time, *Journal of Housing Research* 16(1), 33-46.

Shiller, R., 2000, *Irrational Exuberance*, Princeton University Press, Princeton.

Shum, M., W. Sun and G. Ye, 2014, Superstition and "Lucky" Apartments: Evidence from Transaction-Level Data, *Journal of Comparative Economics* 42(1), 109-117.

Simmons, L. C. and R. M. Schindler, 2003, Cultural Superstitions and the Price Endings used in Chinese Advertising, *Journal of International Marketing* 11(2), 101-111.

Sopranzetti, B.J. and V. Datar, 2002, Price Clustering in Foreign Exchange Spot Markets, *Journal of Financial Markets*, 5(4), 411-417.

Twedt, D. W., 1965, Does the "9 fixation" in retail pricing really promote sales, *Journal of Marketing* 29(4), 54-55.

Tables

Table 1

Summary Statistics

	Mean	Max.	Min.	Std. Dev.
Panel A: Transaction Details				
Nominal Price (HK$ Mil.)	4.69	28.05	0.64	2.43
Sales per year	866.12	2,152.00	161.00	500.47
Panel B: Property Attributes				
Floor level	14.82	30.00	1.00	7.73
- Proportion on lucky floor (%)	10.02	-	-	-
- Proportion on unlucky floor (%)	11.45	-	-	-
Age (years)	19.26	39.31	4.10	7.58
Saleable Floor Area (sqft)	704.50	2142.00	303.00	160.15
Sea-View (proportion, %)	12.13	-	-	-
Top-floor (proportion, %)	4.27	-	-	-
Phase	4.99	9.00	1.00	2.67

Table 2

List Price Endings

Thousand Digit	Including zero		Excluding zero	
	Observations	Percentage	Observations	Percentage
0	20,101	89.3	-	-
1	15	0.1	15	0.6
2	62	0.3	62	2.6
3	145	0.6	145	6.0
4	25	0.1	25	1.0
5	672	3.0	672	27.8
6	55	0.2	55	2.3
7	25	0.1	25	1.0
8	1,362	6.0	1,362	56.3
9	57	0.3	57	2.4
All	22,519		2,418	

Table 3

Frequencies of 8 price ending and other non-8 price ending

Thousand Digit	No. of Obs.	Expected
8	1,362	269
	(56.3)	(11.1)
Non-8	1,056	2,149
	(43.7)	(88.9)
All	2,418	2,418

Note: Percentage appears in parentheses.

Table 4

Results of Estimating Equation (1)

Variable	**Coefficient**	***t*-Statistics**
Intercept	-0.537*	-17.252
LuckyP	0.014*	6.178
LuckyF	0.020*	6.652
SFA	0.002*	32.162
SFA^2	-5.55E-07*	-11.427
AGE	-0.025*	-37.545
AGE^2	3.40E-05***	1.959
FL	0.014*	25.112
FL^2	-0.000*	-16.934
SV	0.056*	11.217
TF	0.054*	10.726
Time Dummy Variables	Yes	

Notes: The adjusted R^2 is 0.928; the *F*-Statistic is 927.116; and the number of observations is 22,519.
* Significant at the 1 percent level; ** Significant at the 5 percent level; *** Significant at the 10% level.

Table 5

Results of Estimating Equation (2)

Variable	Coefficient	*t*-Statistics
Intercept	-0.537*	-17.228
LuckyP	0.014*	6.174
UnluckyP	-0.020	-0.605
LuckyF	0.019*	6.488
UnluckyF	-0.003	-1.323
SFA	0.002*	32.165
SFA^2	-5.55E-07*	-11.428
AGE	-0.025*	-37.539
AGE^2	3.40E-05***	1.959
FL	0.013*	24.868
FL^2	-0.000*	-16.764
SV	0.056*	11.225
TF	0.054*	10.636
Time Dummy Variables	Yes	

Notes: The adjusted R^2 is 0.928; the *F*-Statistic is 921.247; and the number of observations is 22,519.
* Significant at the 1 percent level; ** Significant at the 5 percent level; *** Significant at the 10% level.

Table 6

Results of Estimating Equation (3)

Variable	Coefficient	*t*-Statistics
Intercept	-0.495*	-17.515
LuckyP	0.015*	6.237
LuckyP*UP	-0.015	-1.200
LuckyP*DN	-0.008	-0.951
UnluckyP	-0.020	-0.604
LuckyF	0.018*	5.488
LuckyF*UP	0.026*	2.900
LuckyF*DN	0.004	0.436
UnluckyF	-0.003	-1.353
SFA	0.002*	32.205
SFA^2	-5.56E-07*	-11.464
AGE	-0.025*	-37.823
AGE^2	3.74E-05**	2.157
FL	0.013*	24.827
FL^2	-0.000*	-16.730
SV	0.057*	11.239
TF	0.054*	10.589
Time Dummy Variables	Yes	

Notes: The adjusted R^2 is 0.927; the *F*-Statistic is 906.795; and the number of observation is 22,519.
* Significant at the 1 percent level; ** Significant at the 5 percent level; *** Significant at the 10% level.

Figures

Figure 1

Location of Taikoo Shing Estate (shown in red marker)

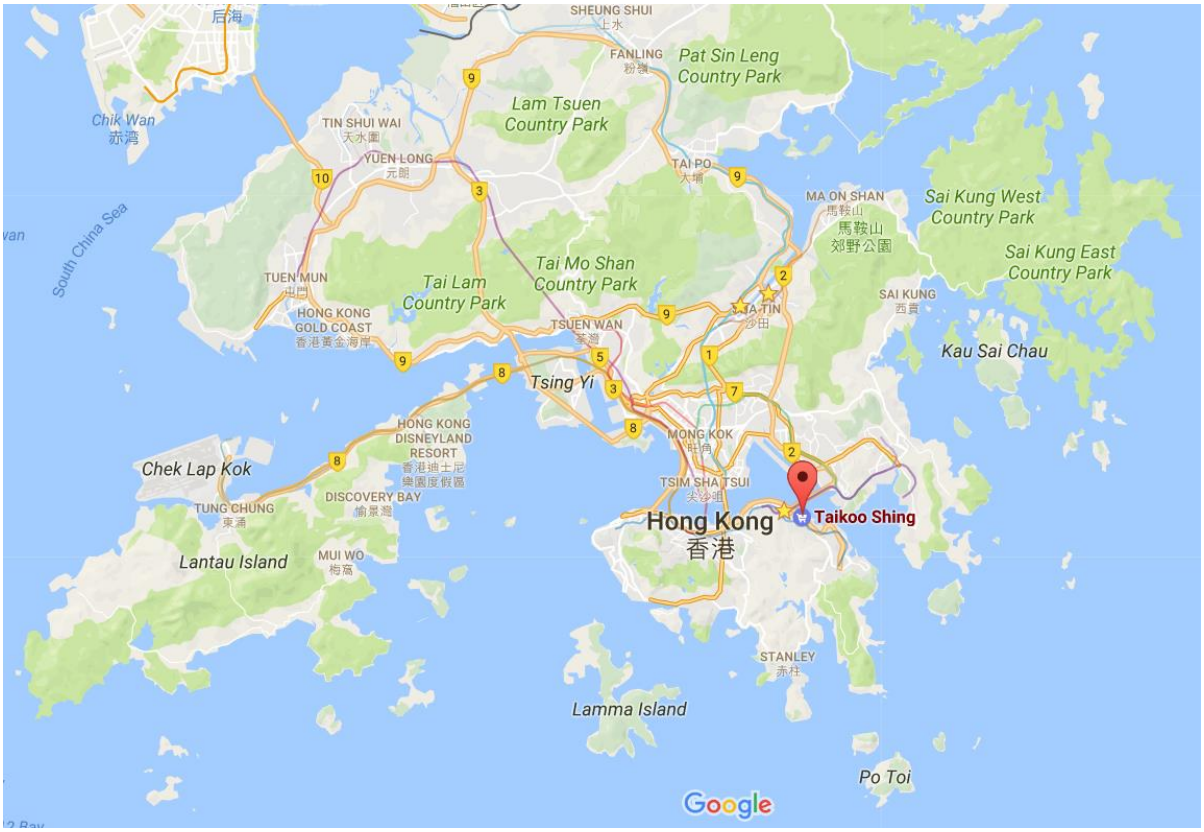
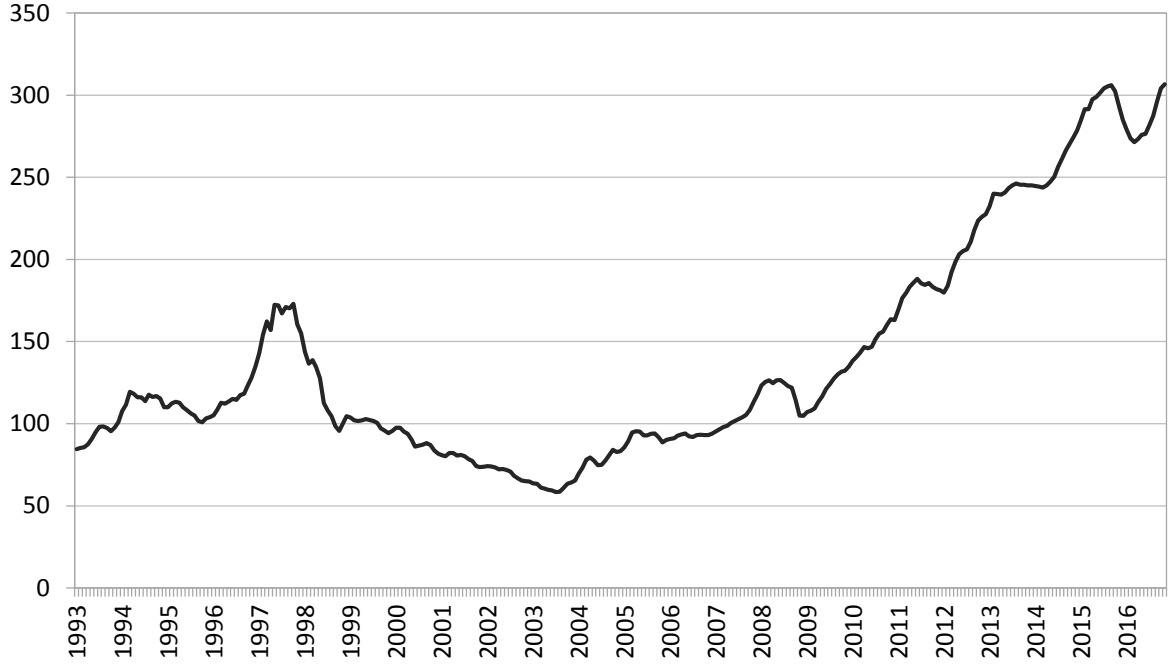


Image source: Google Map

Figure 2

Hong Kong Private Residential Property Price Index, 1991 to 2016 (1999 =100)



Source: Rating and Valuation Department, The Government of Hong Kong SAR (2017)

Figure 3

Boom/bust periods of private housing estate in Hong Kong estimated using HP Filter