INTERNATIONAL REAL ESTATE REVIEW

2021 Vol. 24 No. 4: pp. 549 – 576

Evaluating Different Housing Prices: Marketing and Financial Distortions

Josep Maria Raya[1]
Escola Superior de Ciències Socials i de l'Empresa (Tecnocampus, Universitat Pompeu Fabra). C/Ernest Lluch 32, 08302 Mataró (Barcelona)
Email: josep.raya@upf.edu

The aim of this paper is to evaluate the importance of housing price. We compare the evolution of three different types of housing prices (list, sale and appraisal prices). The objective is to see the marketing and financial consequences of using each type of housing price. To do this, a dataset of a real estate company and its financial intermediary with all of these types of housing prices is used. We estimate econometric models in which the dependent variables are: price (appraisal, selling or list), mark-up, loan to value and foreclosures. The results show evidence of the consequences of using a specific housing price in terms of inflation calculation, financial assets, and collateral valuation and mortgage default, among others.

Keywords

housing prices, appraisal prices, selling prices, markup, default, left-digit bias, inflation, overappraisal, evaluation.

JEL: R31, R21.

---

[1]This work was supported by the Spanish Ministry of Economy and Competitiveness under Grant No. ECO2016-78816R. The authors declare that they have no conflicts of interest. Author's **ORCID:**0000-0002-2885-234X

1. Introduction

In general, housing prices are crucial elements in academic research work that aims to gain a better understanding of the housing market and investigate issues of societal relevance. Housing prices provide the basic data for public policies and the finance sector. Additionally, housing prices are a fundamental instrument of macroprudential policy (Berry and Dalton, 2004).

In the housing market, different types of prices coexist. The selling price is the product of negotiation between sellers and buyers, for which there are two starting prices: the list price, i.e., the price at which the seller is willing to sell his/her property, which would be the initial price of the negotiation, and the price that the buyer is willing to pay, which is not available. Additionally, housing prices can be interpreted as the appraisal prices. The appraisal is supposed to be an objective and expert valuation of a house to strengthen or make a mortgage safer and more marketable. Finally, housing prices can be measured by owner estimations.

In addition, these housing prices affect the economic outcomes of the housing market. For instance, we replicate the situation that occurred at the start of the last financial crisis in Spain. During the boom period (2005–2008), higher growth rates of housing prices were an expectation of future positive returns. This fact increased both transactions and volume. Owners listed their properties at higher prices. In the boom years, the appraisal values went up to clearly above the market price. This was then increased in magnitude by the fact that appraisal firms generally used list prices, and not market prices, to construct the set of comparables (usually six) that are considered as the basis for the pricing of comparable houses in a neighborhood (main pricing methodology for appraisals). If a housing price index is calculated by using appraisals, the aggregated price index also has a bias towards a rapid growth rate, which gives the impression that housing prices are growing faster than they actually are. The appearance of a rapid growth rate of official house prices in the media, attracts some large and many small private investors. Moreover, many families are led to believe that if they do not buy quickly, house prices will be unattainable in the future. These families then go into debt, which contributes to a housing bubble that may end in a financial crisis.

Despite the aforementioned effects of the different housing prices, little attention has been given to the effect of the type of housing price used (DiPasquale and Somerville, 1995; Goodman Jr and Ittner, 1992; Ihlanfeldt and Martinez-Vazquez, 1986; Steele and Goy, 2002). Usually, researchers focus on the differences between selling prices and owner estimates. DiPasquale and Somerville (1995) indicate that price series based on selling prices and owner-reported values have quite similar time-series patterns, although they can differ near market turning points and price levels. Owner value estimates are consistently higher than reported transaction prices. Similarly, Goodman Jr and

Ittner (1992) find that the average U.S. homeowner overestimates the value of his or her house by 6%. Steele and Goy (2002) indicate that this overestimation by owners affects the difference in the valuation of properties in stock (valuated by owner estimation) and sold (valuated by selling price).

The main contribution of this paper is to compare the evolution and interaction of three types of prices, which are largely absent in the literature: list, sale and appraisal prices. The data show that the level and evolution of the different prices are not coincident. The objective of this study is to examine the marketing and financial consequences of their interaction and the use of each type of price. We can break down this main contribution into two parts, depending on the interaction analyzed.

First, we analyze the interaction between selling and appraisal prices. Additionally, selling prices affect appraisal prices. Clayton and Hamilton (1999) note that appraisal values lag behind those in actual market conditions. Although the appraisal price is supposed to be objective and an expert valuation of the house value, appraisals may be subject to bias, as reported by a growing number of studies in this area (Agarwal, Ben-David and Yao, 2014b; Calem, Lambie-Hanson and Nakamura, 2015; Nakamura, 2010). In particular, home buyers/borrowers are greatly incentivized to see appraisals at their maximum value to qualify for as large a loan as possible as independent verification of a fair price. Sellers and brokers would happily accept high appraisals to close a sale and avoid the costs of further marketing the property. These incentives contribute to the possibility that the appraisal price of a house can be significantly higher than its true value. The prevalence of overappraisals documented during the boom years in Spain (Akin *et al*., 2014; Bover, Torrado and Villanueva, 2019) underscores this tendency. In fact, appraisal prices are more affected by financial conditions and overappraisal is used as a mechanism to circumvent financial regulations (Montalvo and Raya, 2018). In this paper, we present additional evidence that appraisal prices do not reflect selling prices. In this sense, this is the first paper that compares the hedonic estimations of the list, selling and appraisal prices. Rosen (1974) shows how heterogeneous products have different characteristics and the marginal price implicit in these characteristics can be known by estimating a model (hedonic price model) that accounts for the price of a product in terms of its characteristics. Clearly, housing is a good that fits perfectly into the framework of hedonic price models. While differences between the hedonic price equations of the selling and list prices show slightly different valuations between the seller and the buyer, hedonic price equations of appraisals show very different valuations of appraisers with respect to those of the sellers and buyers.

As a result of this phenomenon, although Carrillo, Doerner, and Larson (2018) note that authorities can make use of markups as an additional indicator correlated with default, we present evidence that, in the case of overappraisal and a loan to value (LTV) using appraisal price as a denominator, neither markups nor LTV help to predict the default. In this sense, this paper also contributes to a growing body of literature concerned with how the mispricing of assets affects immediate valuations and subsequent performance outcomes such as default risks (Deng, Quigley and Van Order, 2000; Foote, Gerardi and Willen, 2008; Mayer, Pence and Sherlund, 2009; Piskorski, Seru and Vig, 2010)

Second, we analyze the interaction between the list and selling prices. The difference between both prices is the price cut or discount. Anglin, Rutherford and Springer (2003) and Arnold (1999) highlight the importance of setting an optimal list price to maximize the selling price. Therefore, understanding the relationship between the list and selling prices has obvious marketing implications. The list price affects the selling price. According to the prospect theory (Kahneman and Tversky, 1979) when applied to the housing market (Genesove and Mayer, 2001), loss-averse agents consider the original purchase as a reference point. In this case, the original purchase price acts as a reservation price (endowment effect) to avoid losses. Additionally, the list price could serve as an anchor or heuristic used by a buyer to judge the property value, and the buyer may not be able to adjust sufficiently away from the anchor price to arrive at a fair market price (Northcraft and Neale, 1987). Recently, Chava and Yao (2017) show that there is a left digit effect for properties. They compare housing that are listed with a difference of only $100 and find housing listed at prices with smaller left digits are sold at a 0.1% higher price, or $431. Similarly, Repetto and Solís (2019) study a form of inattention known as left-digit bias, which is defined as the inability of some buyers to process prices correctly. Left-digit bias is the propensity to focus on the leftmost digit of a number while partially neglecting the other digits (e.g., the buyer perceives a price of $3.99 to be much lower than the round price of $4). They state that "apartments listed at just-below asking prices are sold at a 3%–5% higher final price after an auction" (Repetto and Solís, 2019). In this paper, we present new evidence of a left-digit bias in the Spanish housing market. The effect of this left-digit bias is measured for the first time in terms of price cuts rather than selling prices. The idiosyncratic aspect of price cuts and markups is pointed out either for the case of mental accounting or in marketing strategies.

To perform this analysis, we use data from the Spanish housing market from 2004 to 2010. The dataset comes from a real estate company and its financial intermediary and contains the three types of housing prices. The economy of Spain during the boom years offers an excellent setting to analyze these questions. Spain, a bank-dominated economy, suffered one of the largest booms and busts in the housing and credit market over the last 20 years. During this period of time, Spain exhibited overly soft lending standards and excessive risk-taking (a behavior made possible by overappraising). At the peak, household mortgages were 65% of the gross domestic product (GDP), and loans to real estate developers and construction firms accounted for another 45% of the GDP. Therefore, the size of the loan pool related directly to real estate activities (production and transactions) amounted to more than 100% of the GDP. Moreover, household debt in Spain (loans to households for mortgages and consumer credit) was 91% of the GDP in 2010, which was just below the 106% in the United Kingdom (UK) and 95% in the United States (U.S.), but substantially higher than the household debt in France and Germany, at 69% and 64%, respectively

This paper is structured as follows. First, we present the Spanish framework. Then, we present the data. Next, we present the models estimated to address previous questions in terms of marketing and financial issues. In this section, we analyze the interaction between appraisal and selling prices as well as that between the selling and list prices. Finally, we present the main results. We end with some concluding remarks and policy implications.

2. Spanish Framework

From 1998 to 2007, Spain experienced one of the most significant housing booms among the developed economies, which was one of the main engines of economic growth in Spain. During that period of time, more dwellings were built in Spain than in Germany, France or Italy. For instance, according to the official statistics of the Departamento de Obras Públicas (Department of Public Works (DPW)), the construction of 860,000 dwellings started in 2006. The average number of conceded mortgages was more than 1.1 million each year. These amounts are quite remarkable if we consider that the annual average number of households in that period was 15.5 million in Spain. Greater competitive pressure implied that managers of financial institutions could only drastically increase profits by originating a large number of new mortgages. Both the softening of credit standards and the extreme dependence on the housing industry led to the financial and economic crisis hitting Spain more harshly than in other countries. During this crisis, one of the main problems for financial institutions was that risky mortgages as well as properties with inflated prices were registered on their balance sheets.

At the same time, the twelve-fold increase in the total value of mortgage debt held by families in Spain emerged as an important issue that needed to be addressed. Higher household debt coupled with a rapid increase in the unemployment rate led to a growing number of families who were unable to service their mortgage debt (Gutiérrez and Delclòs, 2016). Consequently, the number of foreclosures grew exponentially. Spanish mortgages are loans with full recourse. In the event of a mortgage foreclosure, borrowers still hold debt which consists of the outstanding mortgage debt minus the auction price of the home plus interest for late payment, which is generally quite high. Thus, many families not only lost their homes but were also still indebted to the banks. The Spanish government has taken some measures to rectify this situation, such as a "code of good banking practices" and "urgent measures to strengthen protection for mortgage holders” (Royal Decree-Law 27/2012). In 2013, the government created a social housing fund (Law 1/2013), that consisted of approximately 6,000 homes voluntarily supplied by 33 banks to provide affordable housing to evicted families, particularly those with children or family members with special needs (Pareja-Eastaway and Sánchez-Martínez, 2016).

During the period of the crisis, and despite the importance of the construction and housing sectors, there was no good measure to address the changes in the housing prices in Spain. Since 1987, the official housing prices published by the DPW has used, as the basic input, the appraisal price calculated for the purpose of requesting a mortgage. This indicator does not include hedonic correction on the characteristics of the appraisal price of the dwellings in every period.

3. Data

To construct our dataset, we combine information from two different sources. First, we obtain market information from a residential real estate intermediary with branches in most of the Spanish provinces. To gain a sense of the size of this company, we compare its sales with market transactions. The company made approximately 4% of the total sales of homes in the free market in Spain during that year. We matched those residential units with information on the financial intermediary that provided the mortgage. Therefore, house price data are merged with mortgage origination at the loan-level. The data, which correspond to residential mortgages that originated between 2005 and 2010, include information on appraisal value. From a sample of 3,307 observations, we match this information with the information on the financial intermediary. For these houses, we thus have, the three types of housing; i.e., the list, selling and appraisal prices, and prices as well as the characteristics and location of the dwelling. As for dwelling characteristics, we have information about the area (in square meters), age (in years), floors, number of rooms, availability of a lift, external condition of the dwelling, number of parking spaces and the coastal conditions of the municipality. Monthly time dummies identify the month and year in which the dwelling was sold, and location dummies identify the postal codes in which the dwelling is located. These variables are used for both hedonic and price-cut models.

Our data are not strictly representative of the universe of houses sold during the Spanish bubble period. The intermediary that provided the information is not uniformly represented in Spain. It has more branches in large cities and metropolitan areas around large cities. In addition, our sample does not cover the entire distribution of house prices. We missed the upper part of the distribution. For instance, in the city of Barcelona, there are no observations on Pedralbes, which is the neighborhood with the highest housing prices.

However, this does not seem to affect the average price. Table A1 shows a comparison of the appraisal prices of our dataset with those obtained from the DPW for the cities where the housing market intermediary has a very large sample. An appraisal price is the only variable that we can compare with a population variable (in fact, the DPW data are not the population of appraisals but are quite close). The table shows a very small deviation in appraisal prices between our sample and the population of appraisals that compiles the DPW. The difference is only 3.2% for the average of these cities. Therefore, and making clear that we are not claiming that our sample is fully representative of the population of all the properties sold during the years under study, we believe there are no reasons to expect that the difference would be much larger in other places not included in the table (except for sampling variability). Note that the price statistics of the DPW do not include the upper tail of the distribution (as it excludes dwellings priced over 1.05 million Euros[2], but we believe that these expensive dwellings (as in the Pedralbes neighborhood in our sample) are not representative.

Table 1 shows the descriptive statistics for each type of price in the sample as well as for the dwelling characteristics. We can observe that the list prices are 5.0% higher than the selling prices (€174,288 versus €165,979). This difference represents the price cut, that is, the result of the negotiation process between the seller and buyer. This figure is very small, because the majority of the observations belong to the boom period when the negotiating power of the buyer was reduced. Furthermore, we observe appraisal prices to be 24.21% higher than the selling prices (€206,156 versus €165,979). This phenomenon is called overappraisal and documented in the Spanish case in Akin *et al.* (2014) and Montalvo and Raya (2018). During the boom period, appraisers had the incentive to introduce an upward bias in the appraisal valuation[3] to satisfy their clients (financial institutions)[4]. As a result, appraisals allowed the borrower to obtain a high mortgage principal by adjusting the actual loan to the value of the mortgage when the borrower did not have enough resources for the down payment or did have the resources but preferred to borrow more, thereby circumventing regulatory restrictions (Montalvo and Raya, 2018).

Additionally, the mortgage origination data provide other important details, such as the loan terms (amount, spread) and mortgagor characteristics (level of education, age, income, marital status, labour situation, nationality, etc.). The combined data are used to estimate traditional mortgage performance models. Table 2 presents the main descriptives.

---

[2] 1€ = 1.13 USD

[3] Additionally, due to the appraisal mechanism (where the comparison with other dwellings from the same neighbourhood is important for basic valuation), this overappraisal generates positive externalities in the appraisal values of the dwellings in the same neighbourhood.

[4] Gwin and Maxam (2002) find that a moral hazard problem can arise if the lender rewards the appraiser with future business for successful appraisals.

Table 1 Mean List, Selling and Appraisal Prices, and Dwelling Characteristics

	Mean (2004-2010)
List price	€174,288
Sell price	€165,979
Appraisal price	€206,156
Rooms	2.78
Area	67.66
Age	35.89
Lift	0.35
Good Conservation	0.78
Outside cond.	0.87
Floors	2.72
Parking	0.12

Table 2a Mortgage Characteristics

	Sample Mean (standard deviation)
Amount of the Loan (€)[1]	171,211[2]
	(70,513)
Loan to Value (%)	87.56
	(18.64)
Spread (%)	0.85
	(0.43)
Reference Interest Rate (% of total)	
RIML (ref)	15.16
Euribor	84.84
Financial Institution (% of total)	
Commercial bank	39.61
Savings bank	51.62
Individually rescued[2]	8.56
FROB (Spanish Executive Resolution Authority) owned	30.65
Other	12.41
Nonbank financial institutions	8.77
Year (% of total)	
2005	52.95
2006	31.29
2007	4.57
2008	2.51
2009	4.6
2010	4.08
Number of Observations	3,307

Notes: [1] Variables are in real terms. [2] 1€ = 1.13 USD

Table 2b Borrower Characteristics

	Sample mean (standard deviation)
Labor status	
Public sector employee	10.32
Private sector employee or self-employed	86.63
Unemployed	3.06
Type of contract	
Permanent	62.17
Temporary	34.77
Marital status	
Married	31.04
Separated	
Single	68.96
Widow	
Education	
Compulsory	54.52
Secondary (non-compulsory)	33.4
University degree	12.07
Joint and several liability (number of debtors under the Same contract)	
One	31.71
Two	57
Three	11.01
Location	
Interior	57.7
Coastal	42.93
Region	
Community of Madrid	27.62
Income in real terms (€ thousands)[1]	1,563 (0.65)
Age	33.77 (9.18)
Number of Observations	3,307

Notes: In percentage for categorical variables. [1] 1€ = 1.13 USD

We also perform an exercise by using 323 homes (out of a total of 3,307) sold by the real estate company that were bank financed for which we have data on the housing stock. Both datasets include the exact address of the home. Therefore, by merging them, we can determine whether each mortgage ended in foreclosure. In all, 20.43% (66) of these homes ended in foreclosure. This figure seems quite high. However, it is worth noting that in this case, the denominator is new mortgages during the peak years of the boom. Finally, we calculate some figures from this small sample in terms of the explanatory variables of our models. As seen in Table 3, the distributions of the explanatory variables are quite similar to the whole sample. For example, although the LTV ratio is slightly lower, the overappraisal is almost identical (as are the income and the percentage of Spaniards, for example). In the small subsample, mortgages have a larger spread and are more often provided by commercial banks, although further evidence is needed to infer a pattern in this regard.

Table 3 Descriptive Statistics of the Foreclosures

	Sample Mean (standard deviation)
Foreclosure-to-population ratio	0.0024
	(0.0024)
Loan-to-appraisal value (%)	96.92
	(26.96)
Spread (%)	1.14
	(0.58)
Appraisal-to-market price (%)	126.83
	(26.53)
Financial institution (% of total)	
Commercial bank	42.31
Savings bank	51.44
Individually bailed out[2]	9.38
FROB (Spanish Executive Resolution Authority)-owned	28.13
Other	9.94
Nonbank financial institutions	6.25
Borrower characteristics	
Type of employment contract	
Permanent	79.59
Temporary	20.41
Education	
Compulsory	48.00
Secondary (non-compulsory)	28.00
University degree	24.00
Number of holders	
One	34.39
Two	37.14
Three	28.57
Spaniard	53.54
Income in real terms (thousand €)[1]	1,733
	(930)
Number of observations	323

Notes: [1]1€ = 1.13 USD

4. Results

In this section, we first show the different evolutionary changes in the different housing prices during the period analyzed. Second, we analyze the interactions among the selling, list and appraisal prices. We show how housing characteristics are also valued differently by sellers, buyers and appraisers, but focus on the relationship between selling and appraisal prices in which the differences are larger. Then, we analyze the interaction between the list and selling prices. The difference between both prices is the price cut or discount. In this respect, we show left-digit bias as an effective price setting strategy. This evidence is in favor of the idiosyncratic conditions for each transaction that may not reflect average market conditions, which are stronger driving factors for determining collateral value. Additionally, unrealistic appraisal valuation will be shown. Finally, we will show the consequences in terms of mortgage default.

4.1. Evolution of housing prices

With our dataset, we estimate a hedonic function model by using ordinary least squares (OLS). We calculate three hedonic price equations from the types of housing prices, Then, we divide the entire period into two subperiods: the boom (2004–2007) and bust (2008–2010)[5] Table 4 presents the results of a quality-adjusted price index for every type of price and subperiod.

Once price indices are adjusted for quality, it can be clearly observed that the growth rate of the appraisal price is two percentage points higher with respect to selling price, and the growth rate of the list price is clearly higher, which reflects the higher expectations of the sellers. In both the boom and the bust periods, the growth rates of the list prices are clearly higher (approximately seven percentage points)[6]. This difference can be explained by the overestimated expectations of the sellers and expectations that were above the real situation of the market. Montalvo (2006) points out unrealistic expectations about the future expected yield of housing in Spain during the boom period. The economic theory also explains this result. Genesove and Mayer (2001) show that loss-averse agents consider the original purchase as a reference point (reservation price) and set a higher list price. This fact denotes a greater adjustment in terms of selling prices.

[5] The turning point in bank liquidity, credit and real estate dynamics starts in the last quarter of 2007. The tightening of lending conditions came in Spain, as in the whole Euro Area, in the last months of 2007 (see Maddaloni and Peydró, 2011).

[6] In fact, this difference is not statistically significant. We have performed an equality of coefficients test among the equations. In the boom period, we cannot reject the equality of growth rates in selling appraisal prices (chi-squared=1.59). We can reject (at the 1% level of significance) the equality of growth rates among list price and selling price (chi-squared=46.25***) and among list price and appraisal price (chi-squared=12.69***).

Additionally, during the bust period, appraisers were more reluctant to lower prices, especially at the beginning. Thus, appraisal prices were reduced by 10.9% in 2008, while selling and list prices were reduced by 17.7%. At the end of this period, the reduction of the price index in the selling price is higher at 6 percentage points with respect to appraisal prices[7]. In the case of the appraisal prices, the reason is the reluctance to decrease prices at the beginning of the bust period. Therefore, while appraisal prices are only approximately 7 percentage points lower in 2010 with respect to 2004, selling prices are almost 13 percentage points lower. Thus, since the official housing price calculated by the Spanish Ministry is a price index that uses appraisal prices, it can be observed that this type of price index slightly overestimates the growth rate of housing prices calculated with sales price data by 7 percentage points.

Table 4 Accumulated Growth Rates of the Housing Price Indices (2004-2010)

	List price (%)	Selling price (%)	Appraisal price (%)
QAHPI (OLS): 2004-2007	28.27	19.00	21.08
QAHPI (OLS): 2008-2010	-35.81	-32.83	-27.66

4.2. Different effects of property characteristics on the selling and appraisal prices

Appraisal companies quite often pay attention to previously valued prices, which then results in biased valuations (Tidwell and Gallimore, 2014). Since appraisers use a version of the hedonic procedure to set the appraisal value of the dwellings based on the price and characteristics of other dwellings sold in the same area, it is interesting to determine whether the pricing is similar to that offered by the market price. For this purpose, we present in Table 5 the hedonic regressions that have allowed us to obtain the price indices presented in Table 4. Each column corresponds to a model in which the dependent variable is a different housing price: appraisal, selling or list price. In all cases, we estimate the hedonic price models by using dwelling characteristics as the explanatory variables. Monthly time dummies identify the month in which the dwelling was sold. Postal code location dummies identify the location of the dwelling sold. The estimation uses OLS with clustered standard errors at the province level.

[7] Again, we perform an equality of coefficients test among the equations. This difference is statistically significant (chi-squared=30.34***). However, the difference between the list and selling prices in this period is not statistically significant.

$$\begin{aligned} Price_i = \alpha + \beta_1 Rooms_i + \beta_2 Size_i + \beta_3 Age_i + \beta_4 Lift_i + \beta_5 State_i \\ +\beta_6 Outside_i + \beta_7 Floor_i + \beta_8 Parking_i + \beta_9 Coastal_i \\ +\Sigma\beta_{10t} Time_t + \Sigma\beta_{11j} Location_{ij} + u_i \end{aligned} \tag{1}$$

Table 5 shows the results of estimating the hedonic equations. In the first column, we show the coefficients for the equation in which the dependent variable is the appraisal value, while in the second column, the dependent variable is the market price. Significant coefficients are larger for the market price equation than the appraisal price specification. The effects of size, availability of a lift, state of conservation, outside conditions and parking[8] are, in absolute values, higher for market prices. This means that market prices are more sensitive to dwelling and location characteristics than appraisal prices. That is, appraisals do not reflect market price behavior. Furthermore, the goodness-of-fit indicator shows that while explanatory values explain for 79% of the variability of the selling price, they explain for 68% of the variability of the appraisal price. Both results can be interpreted as additional evidence that appraisal prices are more affected by other elements, such as financial conditions.

Comparing the selling and list price equations, the differences in coefficients are, in this case, the result of different valuations between the seller and the buyer. With this interpretation, sellers place a greater value on the area of the house and the number of floors[9].

4.3. Price setting

In this section, we analyze the interaction between the selling and list prices. The difference between the two prices is the price cut or discount. A significant number of apartments are listed at a 10-thousand threshold (12.2%)[10]. Additionally, a large number of dwellings are listed at a price just below one threshold. Is the price cut of these dwellings listed at a threshold higher than that of dwellings priced out of the threshold? A positive answer to this question implies that they are subject to first-digit bias; that is, buyers incorrectly

[8] The difference between the coefficients in the appraisal and selling price equations is statistically significant at the 1% level (with the exception of the ones from the variable parking spaces, for which the difference is significant at the 5% level). The difference in the case of a coastal area is not statistically significant. We reach this conclusion by performing an equality of coefficients chi-squared test among the equations.

[9] The difference between the coefficients in the list and selling price equations is statistically significant at the 5% level. In the other cases, the difference observed is not statistically significant.

[10] For example, €240,000 vs. €250,000 (1€ = 1.13 USD) and 37.7% of the dwellings are listed at the one-thousand threshold. For example, €240,000 vs. €241,000 (1€ = 1.13 USD).

perceive these dwellings as more expensive because they tend to ignore, at least partially, the part of the number to the right of the first digit.

Table 5 Estimated Price Models

	Appraisal Coef.	Selling Coef.	List Coef.
Rooms	0.007	0.005	0.006
Area	0.008***	0.008***	0.009***
Age	-0.000	-0.000	-0.000
Lift	0.086***	0.126***	0.129***
Conservation	0.040***	0.091***	0.086***
Outside cond.	0.028**	0.040***	0.045***
Floors	0.005***	0.001	0.003**
Parking	0.020***	0.032*	0.033*
Coastal	0.419***	0.458***	-0.089*
Intercept	11.383***	10.935***	10.913***
Time dummies	YES	YES	YES
Location dummies	YES	YES	YES
N	3,307	3,307	3,307
R-squared	0,68	0,79	0,81

Note: Each column corresponds to a model in which the dependent variable is a different housing price: appraisal, selling or list price. In all cases, we estimate hedonic price models by using dwelling characteristics as explanatory variables. Monthly time dummies identify the month in which the dwelling was sold. Postal code location dummies identify the location of the dwelling sold. Errors are clustered at province level. Significance: *** p<0.01, ** p<0.05, and * p<0.1

A natural way of testing for the presence of left-digit bias in our context is to compare the price cuts of dwellings listed exactly at one threshold to those that are out of the threshold. Mean differences in price cut seem to support this hypothesis. Thus, the price cut is higher (7.86 versus 4.41 percentage points) in dwellings listed at a 10-thousand threshold. However, we must be able to reasonably rule out that there are no unobservable characteristics of apartments that are correlated with the decision to list them on either side of the threshold. For example, this issue arises if some sellers (or real estate agents) systematically choose asking prices at the threshold for worse apartments. Our identification strategy relies on comparing apartments that are similar in terms of characteristics and location. In the absence of evidence on sorting in the previous tests, we interpret a higher price cut of prices in the threshold as evidence of buyers who suffer from first-digit bias. To this end, in the first column of Table 6, we present the same model estimated in Table 5 with two differences. First, the dependent variable is now price cut. Second, we add a dummy variable that takes the value of 1 in the case of a listed price in a 10-thousand threshold and 0 in the case of a price just below the threshold. The results show that after controlling for the dwelling characteristics and location, first-digit bias persists. Dwellings at the 10-thousand threshold have almost a 1 percentage point higher of a price cut (approximately €1,660). In the other two columns, we add the appraisal price (second column) and individual buyer characteristics (third column) as the control. The results remain the same[11].

In line with Repetto and Solís (2019), we interpret a higher cut of prices in the threshold as evidence of buyers who are suffering from first-digit bias. However, there is room for additional explanations that complement left-digit bias. In this sense, as the list price is a highly strategic decision, a seller who chooses the list price on the exact threshold would be leaving some room for negotiation, while a seller with an off-threshold price would show that s/he is not willing to negotiate on the price. With our dataset, we cannot disentangle between these two explanations.

Table 6 Price Setting Models

	Model 1 Coef./se	Model 2 Coef./se	Model 3 Coef./se
Listed at 10-thousand threshold	0.969^{***}	1.133^{***}	1.367^{***}
Time dummies	YES	YES	YES
Location dummies	YES	YES	YES
Appraisal price	NO	YES	NO
Individual characteristics	NO	NO	YES
N	3,307	3,307	3,307
R-squared	0.27	0.28	0.28

Note: Each column corresponds to a model in which the dependent variable is price cut. In all cases, the dwelling characteristics are explanatory variables. Monthly time dummies identify the month in which the dwelling was sold. Postal code location dummies identify the location of the dwelling sold. Model 1 is the baseline model. Model 2 also includes appraisal price as an explanatory variable. Model 3 adds to the individual characteristics of Model 1. Errors are clustered at the province level. Significance: *** p<0.01, ** p<0.05, and * p<0.1.

4.4. Markup as a predictor of mortgage defaults

The housing market is characterized by major information asymmetries, heterogeneous preferences, and high transaction costs. Accordingly, the effective spread for housing is large, and the prices at which buyers and sellers are willing to trade vary widely relative to the average market price, even after controlling for location, and observable house and borrower characteristics. The previous sections in this study have documented that the sellers, buyers

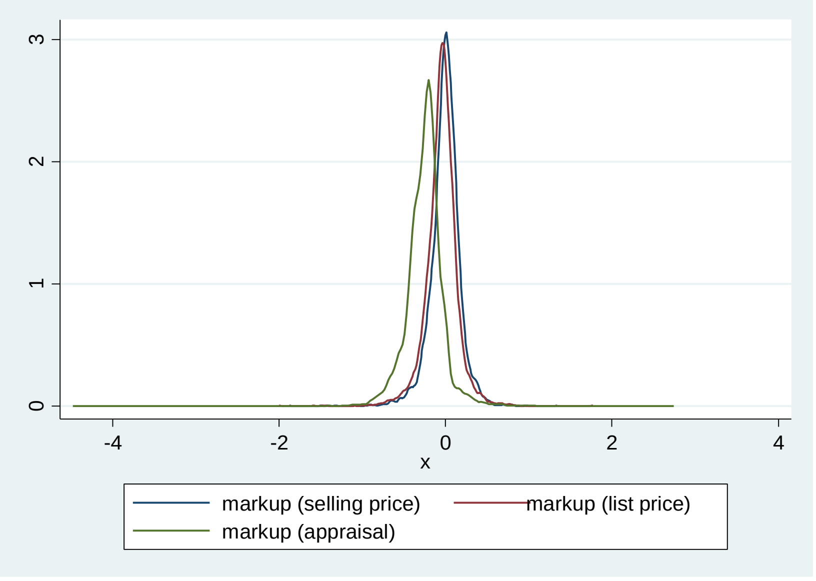
---

[11] Table A2 present similar results that consider dwellings listed at a 1-thousand threshold. The results are similar. First-digit bias ranges from 0.83 to 1.27 percentage points depending on the specification.

and appraisers value the same housing characteristics differently and the final sales price depends on the idiosyncratic conditions of the transaction, such as strategic behaviors in price settings. In this sense, not only do markups (i.e., the difference between transaction and the expected prices) tend to be large but also as housing is highly leveraged, individual mortgage performance is sensitive to variations in the value of the collateral on the loan. In particular, Carrillo, Doerner, and Larson (2018) show that markup mechanically determines future equity value and, thus, is a key determinant of mortgage performance. Higher markups imply higher risk.

The markup is calculated as the percentage difference between the observed and predicted transaction prices. Intuitively, the markup resembles (but is not identical to) a residual from a hedonic sales regression. We also calculate markup as the percentage difference between the observed transaction and appraisal prices. See the kernel densities of the three markups in Figure 1. As can be observed, markups that use appraisal value shift to the left as a consequence of overappraisal.

Figure 1 Kernel Density of Markups



We estimate models on the determinants of loans to transaction prices. Note that LTV equations are models that approximate the probability of future default because the correlation between the LTV ratio (LTV) and the future probability of default is well known (Wong et al., 2011). However, this is only true in the case of a correct valuation of the collateral. In the presence of a markup, the sales price captures conditions that are idiosyncratic to each transaction and that may not reflect average market conditions. Average rather than idiosyncratic conditions should be stronger driving factors for determining collateral value. Therefore, our empirical strategy consists of estimating reduced-form equations on the determinants of LTV, where LTV is the loan to transaction (LTT) price. The loan principal is chosen by the bank (in this sense, it can be endogenous), whereas the transaction value is not endogenous. All the equations are estimated for the period of 2005 to 2010. In all cases, we include location (postal code) and monthly time dummies. Additionally, we include a dummy that identifies the financial institution that granted the mortgage. We add spread and borrower characteristics. All in all, we estimate this specification:

$$\begin{aligned} LTT_i = \alpha &+ \beta_0 Markup_i + \beta_1 Borrower\ Characteristics_i \\ &+ \Sigma\beta_{2k} Financial\ institution_{ik} \\ &+ \beta_3 Benchmark\ reference\ interest\ rate_i + \beta_4 Spread_i \\ &+ \Sigma\beta_{6t} Time_t + \Sigma\beta_{7j} Location_{ij} \end{aligned} \tag{2}$$

Before commenting on the results in Table 7, some intuition is required. In this exercise, markup is defined as the selling price minus the appraisal price, and the LTV is the loan-to-selling price ratio. Therefore, a higher selling price (than the appraisal value) will increase the markup and decrease the LTV, but only if the loan amount does not increase more than the selling price. In Table 7, we see that markup is a negative factor of the LTV. A 1% higher markup decreases the LTV by 17.55 percentage points (15.99 percentage points if the markup is calculated using list prices). All else equal, a higher markup implies an "artificially" lower LTV. Does this imply a lower probability of default? Suppose a 10% markup on a 95-LTV loan could result in an underwater mortgage at origination, with the actual LTV of the loan being 105. We have no information on the effective default of these loans in the future. However, we know for a very small subsample whether the dwelling ends in foreclosure. Table 8 presents an estimation of the importance of markup on the probability of foreclosure. Due to the sample size, the coefficient is not statistically significant, but a higher markup implies a higher probability of foreclosure. With a positive markup, the LTV understates the default risk.

Additionally, we calculate the models of the determinants of loans to appraisal. In this case, a higher selling price (than appraisal value) will increase the markup. First, this fact does not mean that the appraisal value is decreasing (only that the increase is lower than that observed in the selling prices) and the loan to appraisal can either be increased or reduced, depending on whether the loan amount has increased more or less. The results provide evidence that markups can predict future loans to appraisal. Thus, an LTV is 8.4 percentage points higher for a 1% selling markup (8.7 if the markup is calculated with respect to the list prices), conditional on the covariates. Markups and LTV

Table 7 Effects of Markups on LTV

	LTV (Loan to Selling)		LTV (Loan to Appraisal)	
Markup	-17.55***	-15.99***	8.407**	8.657**
Coastal	1.966	2.166	2.024	1.934
Spread	5.755***	5.842***	1.995	1.984
Education				
Secondary school	-1.370	-1.439	-0.908	-0.861
University degree	-2.691	-2.919	-1.113	-1.000
Age	-0.192	-0.208	-0.148	-0.139
Age2	-0.00179	-0.00161	0.0000689	-0.0000317
Number of debtors				
Two	6.280***	6.168***	3.832***	3.855***
Three	10.98***	10.61***	5.629***	5.740***
Spanish	-3.868**	-3.960**	-1.808	-1.752
Marital Status				
Married	1.289	1.397	1.188	1.132
Labor status				
Public sector	-2.874	-2.821	-1.670	-1.690
Unemployed	-2.507	-2.223	-1.990	-2.126
Type of contract				
Permanent	-0.819	-0.748	-0.385	-0.420
Income in real terms	1.815*	1.772*	-0.259	-0.249
Euribor	-8.822***	-8.867***	-3.832	-3.876
Intercept	117.8***	118.4***	90.68***	90.40***
	(18.35)	(18.43)	(16.34)	(16.28)
LOCATION DUMMIES	YES	YES	YES	YES
TIME DUMMIES	YES	YES	YES	YES
FINANTIAL INSTITUTION DUMMIES	YES	YES	YES	YES
N	3,307	3,307	3,307	3,307
R-squared	0.45	0.43	0.35	0.33

Note: Each column corresponds to a model in which the dependent variable is loan to value. In all cases, the characteristics of borrowers and markup are used as the explanatory variables. In the first and third columns, the markup is calculated in terms of the selling price, and in the second and fourth columns, the markup is calculated in terms of the list prices. Monthly time dummies identify the month in which the dwelling was sold. Postal code location dummies identify the location of the dwelling sold. A financial institution dummy identifies the financial institution in which the mortgage is granted. Errors are clustered at the province level. Significance: *** p<0.01, ** p<0.05, and * p<0.1.

exhibit a positive relationship. Due to the positive correlation between markups and default, one could surmise that loans to appraisal are a better predictor of default than loans to transaction prices. In fact, this is the opposite in the Spanish case due to overappraisal. One of the primary purposes of an appraisal is to help to assess the risk of default for both the lender and the borrower. In Table 5, we show evidence for the incorrect valuation of housing characteristics through appraisal. Manually performed (human) appraisals may be subject to bias, as reported by a growing number of studies in this area (Agarwal *et al.*, 2014a; Calem, Lambie-Hanson and Nakamura, 2015; Montalvo and Raya, 2018; Nakamura, 2010). In the descriptive analysis, we find an overappraisal of approximately 30%, which was a typical value during the Spanish boom (Akin *et al.*, 2014; Bover et al., 2019; Montalvo and Raya, 2018). A higher appraisal implies a lower markup and a lower LTV. In this case, neither markup nor LTV helps to predict default. Table 8 shows that a higher markup (calculated as the percentage difference between the observed transaction and appraisal prices) is negatively correlated with the probability of foreclosure.

Table 8 Markup as Determinant of Foreclosure

Dependent variable: Probability of foreclosure			
	(1)	(2)	(3)
Markup (selling)	1.025		
Markup (list)		1.642	
Markup (appraisal)			-1.404
Intercept	-1.277***	-1.218***	-1.562***
	(-6.20)	(-5.60)	(-5.86)
N	323	323	323
R-squared	0.08	0.08	0.09

Note: Each column corresponds to a model in which the dependent variable is the probability of foreclosure. In all cases, markup is the only explanatory variable. Each column corresponds to different definitions of markup depending on the housing price used: (1) selling price, (2) list price and (3) appraisal price. Significance: *** p<0.01, ** p<0.05, and * p<0.1

5. Conclusion

The aim of the paper is to examine the relationships of three prices not analyzed in the literature (list, selling and appraisal prices) since the literature generally focuses on the relationship between selling and owner estimations. The paper breaks down these three types of housing prices and focuses on two interactions among them. First, we analyze the interaction between selling and appraisal prices and its financial consequences. Second, we analyze the interaction between the list and selling prices. The objective is to understand the consequences of using each type of price. To do this, a dataset of a real estate company and its financial intermediary with all three types of housing prices is used.

The first outcome of the paper is that we show that the different types of housing prices evolved differently during the period analyzed. How we measure inflation in the housing component is highly consequential for our understanding of macroeconomic dynamics, monetary policy, and growth. The evolution of the housing prices analyzed is very different from those observed for the housing component in the Spanish Consumer Price Index (CPI). In 2007, the weight of the housing component of the Spanish CPI is 10.71%. This housing component is calculated through the rental equivalent approach, since if housing services are obtained under ownership, then housing is considered an investment good. In particular, the rental equivalence approach values the services yielded by an owned dwelling at the corresponding market rental value for the same sort of dwelling for the same period of time. The price data needed for the CPI rental equivalence component for owner-occupied housing services are observations on rents paid by renters. This has two implications: first, the housing component is underweighted[12], and second, the price growth (and decrease) is much more reduced and stable. Table 9 shows the increase in this rent component rate compared with the growth rate of the annual price with the values obtained in Table 4. The evolution of the growth rate of the rent index in the CPI ranges from 1.12% (2010) to 4.51% (2006). This evolution is more volatile in the case of any of the price indices. For instance, in the case of the selling price, the growth rate ranges from -17.90% (2008) to 11.41% (2006). In addition, while the maximum growth rate occurs in 2006 in both cases, the minimum growth rate is observed with a two-year delay in the case of the rent index of the CPI. Finally, the rent index of the CPI always increases over the period, the accumulated growth is 21.87%, while in the case of price indices, the accumulated growth rate is always negative. The last column of Table 9 shows differences in using the selling price rather than the rent index of the CPI in calculating the CPI. Assuming a constant weight, inflation would have been 0.74 percentage points higher in 2006 and 2.39 percentage points lower in 2008. That is, the CPI is biased[13].

---

[12] Including imputed rent for these dwellings, this weight will increase from 10.71% to 30.22% (using data from the Spanish Family Budget Survey, 2020). In the United States consumer price index, imputed rent accounts for 24% of the total weight.

[13] Arévalo and Ruiz-Castillo (2006) show that dropping nonrental housing services from the CPI creates a downward bias in the measurement of inflation. Our calculated bias for each year must be added to this one.

Table 9 Annual Rent Growth Rate with Respect to the Annual Price Growth Rate

Year	CPI rent	Selling Price	Appraisal Price	List price	Difference in CPI with use of selling price
2005	4.14	9.64	10.63	12.41	0.59
2006	4.51	11.41	8.74	12.57	0.74
2007	4.22	-2.04	1.71	3.29	-0.67
2008	4.39	-17.90	-11.88	-25.43	-2.39
2009	1.79	-11.56	-11.46	-5.50	-1.43
2010	1.12	-3.37	-4.30	-4.84	-0.48
Accumulated growth	21.87	-13.83	-6.57	-7.50	-3.82

Another outcome of the paper is that housing characteristics are also valued differently by sellers, buyers and appraisers. We focus on the differences among sellers and appraisers. In this respect, an unrealistic appraisal valuation has been shown. Appraisal prices are more affected by other elements, such as financial conditions, than by market valuations of dwelling and location characteristics. Market prices are more sensitive to dwelling and location characteristics than appraisal prices. In this sense, appraisal prices do not reflect market price behavior. Thus, appraisal firms owned by banks have generated a perverse incentive that pushes appraisal values up during boom periods, clearly above the market price. In addition, as Montalvo and Raya (2012) point out, bias towards higher housing prices derived from the incentives of appraisal firms is increased by the fact that appraisal firms generally use list prices, not market prices, to construct their appraisals. This result has important economic implications. First, the use of a housing price index based on appraisals as the only official indicator of prices during the bubble years also generates external effects. The bias towards calculating high appraisal values leads to an aggregated price index that also has bias towards a rapid growth rate, which gives the impression that house prices were growing faster than they actually were. Each time that the rapid growth rate of official house prices appeared in the media, private investors (including some small ones) were intrigued. In this sense, Cloyne et al. (2017) point out a positive effect of housing prices on borrowing. Therefore, the use of appraisals for the construction of the official price index feeds a vicious circle that leads to an enormous housing bubble and later to a financial crisis. In addition, appraisal prices do not decrease and are observed to have some delay with respect to market prices. Valuation methods often neglect the inclusion of the natural cyclic behavior of the real estate market, especially in nontransparent markets with very few transactions (d’Amato, 2015). As market value information is not observable, appraisal companies often pay attention to previously valued prices, which frequently results in biased and lagged valuations.

This outcome has important policy implications for financial institutions. During this crisis, one of the main problems for financial institutions[14] is that their balance sheets not only contain risky mortgages but also properties with inflated prices (Montalvo and Raya, 2018). The majority of the Spanish housing stock is from foreclosures (in the case of properties from families) or, in particular, bankruptcies (in the case of properties from construction companies). To illustrate, the net value of property assets (€16.929 billion) provided by financial institutions in their annual reports as well as information on the number of properties sold are used to estimate that there were approximately 216,289 dwellings on the balance sheet of financial institutions at the end of 2013, which represents 25.4% of the housing stock.

The net value of the property assets of the financial institutions is €16.929 billion). This net value is almost 17.76% less than the gross value of the same assets (€19.935 billion). The difference between the two figures is due to depreciation. We argue that this difference between the gross and net values should be higher for two reasons. First, the gross value is, roughly, the appraisal price. As we have pointed out, appraisal prices are inflated by 30% (higher than the previous depreciation percentage). Table 10 shows the overappraisal among 27 financial institutions in the sample. All of the institutions introduce an upward bias, which ranges from 14% to 36%. Overappraisal is slightly higher in the bust period and was statistically higher for the (later) rescued banks (1.30 with respect to 1.25).

Second, these dwellings were commonly purchased (and appraised) during the boom period (2005–2008). Therefore, in the best case scenario, the dwelling was purchased at the beginning of 2005 or end of 2008. In both cases, there is still a depreciation in terms of the market value of 11.56% in 2009 and 3.37% in 2010. That is, an accumulated depreciation of 15.32%. Adding 11.24% (difference between 29% and 17.76%) to this percentage, we find that the real net value of the property assets of the financial institutions was overvalued by 26.56%. That is, the real net value of the market prices of these assets is €12.433 billion). Alternatively, we calculate that the gross value (€19.935 billion) is more than 60.34% higher than the real net value. To verify this figure, we use data from one of the rescued saving banks (Bank 10 of Table 10). For this savings bank, we know the following for a sample of 7,175 dwellings (mean value in brackets): gross value (€237,732), appraisal value (€196,785), net value (€176,082) and transaction price (€142,675). Calculating the ratio between the gross value and the transaction price, the former is higher at 79.81%. Additionally, the net value is overvalued by 31.45% with respect to market prices. In this respect, our valuation is very conservative, and the overvaluation of the Spanish bank balance sheets is enormous.

[14] €61.495 billion was needed to rescue the Spanish financial system.

Table 10 Overappraisal - Distribution Among Financial Institutions

BANK	Whole Overappraisal	Until 2007: II Overappraisal	After 2007: III Overappraisal	Difference
BANK 1	1.30	1.30	1.30	0.00
BANK 2	1.35			
BANK 3	1.31			
BANK 4	1.17			
BANK 5	1.18			
BANK 6	1.29	1.27	1.35	0.08**
BANK 7	1.32			
BANK 8	1.35			
BANK 9	1.23			
BANK 10	1.20			
BANK 11	1.29			
BANK 12	1.25			
BANK 13	1.20			
BANK 14	1.21	1.20	1.29	0.09**
BANK 15	1.30			
BANK 16	1.36			
BANK 17	1.17			
BANK 18	1.34	1.19	1.40	0.21**
BANK 19	1.29	1.28	1.36	0.08**
BANK 20	1.32	1.29	1.34	0.05**
BANK 21	1.19			
BANK 22	1.23			
BANK 23	1.14			
BANK 24	1.21			
BANK 25	1.28			
BANK 26	1.25	1.24	1.27	0.03**
BANK 27	1.36	1.33	1.39	0.06**
All	1.29	1.25	1.31	0.06***

Note: *** p<0.01, ** p<0.05, and * p<0.1

Additionally, we have focused on the interaction between the selling and list prices. In this respect, we have found evidence of left-digit bias as an effective price setting strategy. In the case of properties with similar attributes and location, when listing prices have smaller left digits compared with properties listed at a 10-thousand threshold, they are sold with a 1 percentage point lower price cut. This result holds when we control for appraisal price or buyer characteristics. Our results are in line with those of Chava and Yao (2017) and Repetto and Solís (2019), who highlight how behavioral biases can affect even significant and high-value purchases such as housing. Apartments with asking prices just below receive more attention. In contrast, buyers pay a large price for their inattention. This evidence is in favor of the idiosyncratic conditions for each transaction that may not reflect average market conditions, which are stronger driving factors for determining the collateral value.

Finally, we will show the consequences in terms of mortgage default. With a positive markup, the LTV understates the default risk. Policy implications are obvious. Macroprudential policy must follow not only the LTV but also markup as an indicator of possible mortgage default. Although markups do not cause default, they are correlated through collateral, and LTV can fail when trying to predict default. Additionally, in the case of an overappraisal, the macroprudential policy consists of avoiding appraisals for predicting defaults either as a component of a markup or the LTV.

References

Agarwal, S., Amromin, G., Ben-David, I., Chomsisengphet, S., and Evanoff, D.D. (2014a). Predatory lending and the subprime crisis, *Journal of Financial Economics,* 113(1), 29–52. doi: https://doi.org/10.1016/j.jfineco.2014.02.008

Agarwal, S., Ben-David, I., and Yao, V. (2014b). Systematic Mistakes in the Mortgage Market and Lack of Financial Sophistication SSRN 2548316. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2548316

Akin, O., Montalvo, J.G., García Villar, J., Peydró, J.-L., and Raya, J.M. (2014). The real estate and credit bubble: evidence from Spain, *SERIEs,* 5(2), 223-243. doi: https://doi.org/10.1007/s13209-014-0115-9

Anglin, P.M., Rutherford, R., and Springer, T.M. (2003). The trade-off between the selling price of residential properties and time-on-the-market: The impact of price setting, *The Journal of Real Estate Finance and Economics*, 26(1), 95–111. doi: https://doi.org/10.1023/A:1021526332732

Arévalo, R., and Ruiz-Castillo, J. (2006). On the imputation of rental prices to owner-occupied housing, *Journal of the European Economic Association*, 4(4), 830–861.

Arnold, M.A. (1999). Search, bargaining and optimal asking prices, *Real estate economics*, 27(3), 453–481. doi: https://doi.org/10.1111/1540-6229.00780

Berry, M., and Dalton, T. (2004). Housing prices and policy dilemmas: a peculiarly Australian problem?, *Urban policy and research*, 22(1), 69–91. doi: https://doi.org/10.1080/0811114042000185509

Bover, O., Torrado, M., and Villanueva, E. (2019). The loan to value ratio for housing in Spain over the period 2004-2016, *Banco de Espana Article*, 2, 19. doi: https://dx.doi.org/10.2139/ssrn.3333102

Calem, P.S., Lambie-Hanson, L., and Nakamura, L.I. (2015). Information losses in home purchase appraisals. Federal Reserve Bank of Philadelphia

Working Paper No. 15-11 [Preprint]. Available at: doi: https://dx.doi.org/10.2139/ssrn.2574689

Carrillo, P.E., Doerner, W.M., and Larson, W.D. (2018). House Price Markups and Mortgage Defaults. Federal Housing Finance Agency Working Paper Series No. 18-02 [Preprint]. Available at: https://www.fhfa.gov/PolicyProgramsResearch/Research/PaperDocuments/wp1802.pdf

Chava, S., and Yao, V.W. (2017). *Cognitive Reference Points, the Left-Digit Effect, and Clustering in Housing Markets*. Unpublished.

Clayton, J., and Hamilton, S.W. (1999). Risk and return in the Canadian real estate market, *Canadian Journal of Administrative Sciences/Revue Canadienne des Sciences de l'Administration*, 16(2), 132–148. doi: https://doi.org/10.1111/j.1936-4490.1999.tb00619.x

Cloyne, J., Huber, K., Ilzetzki, E., and Kleven, H. (2017). *The effect of house prices on household borrowing: A new approach*. Cambridge, MA: National Bureau of Economic Research. Unpublished.

d'Amato, M. (2015). Income approach and property market cycle, *International Journal of Strategic Property Management*, 19(3), 207–219. doi: https://doi.org/10.3846/1648715X.2015.1048762

Deng, Y., Quigley, J.M., and Van Order, R. (2000). Mortgage terminations, heterogeneity and the exercise of mortgage options, *Econometrica*, 68(2), 275–307. doi: https://doi.org/10.1111/1468-0262.00110

DiPasquale, D., and Somerville, C.T. (1995). Do house price indices based on transacting units represent the entire stock? Evidence from the American housing survey, *Journal of Housing Economics*, 4(3), 195–229. doi: https://doi.org/10.1006/jhec.1995.1010

Foote, C.L., Gerardi, K., and Willen, P.S. (2008). Negative equity and foreclosure: Theory and evidence, *Journal of Urban Economics*, 64(2), 234–245. doi: https://doi.org/10.1016/j.jue.2008.07.006

Genesove, D., and Mayer, C. (2001). Loss aversion and seller behavior: Evidence from the housing market, T*he Quarterly Journal of Economics*, *116*(4), 1233-1260. doi: https://doi.org/10.1162/003355301753265561

Goodman Jr, J.L., and Ittner, J.B. (1992). The accuracy of home owners' estimates of house value. *Journal of Housing Economics*. 2(4), 339–357. doi: https://doi.org/10.1016/1051-1377(92)90008-E

Gutiérrez, A., and Delclòs, X. (2016). The uneven distribution of evictions as new evidence of urban inequality: A spatial analysis approach in two Catalan cities. *Cities*, 56, 101-108.

Gwin, C.R., and Maxam, C.L. (2002). Why do real estate appraisals nearly always equal offer price? A theoretical justification, *Journal of Property Investment & Finance*, 20(3), 242–253. doi: https://doi.org/10.1108/14635780210433481

Ihlanfeldt, K.R., and Martinez-Vazquez, J. (1986). Alternative value estimates of owner-occupied housing: evidence on sample selection bias and systematic errors, *Journal of Urban Economics*, 20(3), 356–369. doi: https://doi.org/10.1016/0094-1190(86)90025-2

Kahneman, D., and Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk, *Econometrica*, 47(2), 263–291. doi: https://doi.org/10.2307/1914185

Maddaloni, A., and Peydró, J.L. (2011). Bank risk-taking, securitization, supervision, and low interest rates: Evidence from the Euro-area and the US lending standards, *The Review of Financial Studies*, 24(6), 2121–2165. doi: https://doi.org/10.1093/rfs/hhr015

Mayer, C., Pence, K., and Sherlund, S.M. (2009). The rise in mortgage defaults, *Journal of Economic Perspectives*, 23(1), 27–50. doi: https://doi.org/10.1257/jep.23.1.27

Montalvo, J.G. (2006). Deconstruyendo la burbuja: expectativas de revalorización y precio de la vivienda en España, *Papeles de economía española*, 109, 44–75.

Montalvo, J.G., and Raya, J.M. (2012). What is the right price of Spanish residential real estate?, *Spanish Economic and Financial Outlook*, 1, 22–29.

Montalvo, J.G., and Raya, J.M. (2018). Constraints on LTV as a Macroprudential Tool: A Precautionary Tale, *Oxford Economic Papers*, 70(3), 821–845. doi: https://doi.org/10.1093/oep/gpy007

Nakamura, L. (2010). How much is that home really worth? Appraisal bias and house-price uncertainty, *The Business Review*, (Q1), 11–22.

Northcraft, G.B., and Neale, M.A. (1987). Experts, amateurs, and real estate: An anchoring-and-adjustment perspective on property pricing decisions, *Organizational behavior and human decision processes*, 39(1), 84–97. doi: https://doi.org/10.1016/0749-5978(87)90046-X

Pareja-Eastaway, M., and Sánchez-Martínez, T. (2017). Social housing in Spain: what role does the private rented market play? J*ournal of Housing and the Built Environment*, *32(*2), 377-395.

Piskorski, T., Seru, A., and Vig, V. (2010). Securitization and distressed loan renegotiation: Evidence from the subprime mortgage crisis, *Journal of Financial Economics*, 97(3), 369–397. doi: https://doi.org/10.1016/j.jfineco.2010.04.003

Repetto, L., and Solís, A. (2020). The Price of Inattention: Evidence from the Swedish Housing Market, *Journal of the European Economic Association*, 18(6), 3261-3304. doi: https://doi.org/10.1093/jeea/jvz065

Rosen, S. (1974). Hedonic prices and implicit markets: product differentiation in pure competition, *Journal of Political Economy*, 82(1), 34–55. doi: https://doi.org/10.1086/260169

Steele, M., and Goy, R. (2002). Do sales prices overstate underlying house prices in market downturns? Evidence from the Canadian house price crash of 1991, *Canadian Journal of Administrative Sciences/Revue Canadienne des Sciences de l'Administration*, 19(4), 333–345. doi: https://doi.org/10.1111/j.1936-4490.2002.tb00279.x

Tidwell, O.A., and Gallimore, P. (2014). The influence of a decision support tool on real estate valuations, *Journal of Property Research*, 31(1), 45–63. doi: https://doi.org/10.1080/09599916.2013.819519

Wong, T.C, Fong, T., Li, K.F, and Choi, H., (2011). Loan-to-Value Ratio as a Macroprudential Tool - Hong Kong's Experience and Cross-Country Evidence, *Systemic Risk, Basel III, Financial Stability and Regulation 2011*. doi: https://dx.doi.org/10.2139/ssrn.1768546

Appendices

Table A1 Comparison of the Sample with Other Sources

	Growth rate comparison		Price level comparison	
	Transaction price		Appraisal price	
	Our sample	INE (Registered price)	Our sample	Department of Public Works
	%	%	€/m²	€/m²
Barcelona	-21.64	-17.4	2,569	3,103
L'Hospitalet de Llobregat	-31.00	-17.4	1,949	1,647
Madrid	-17.77	-18.5	2,326	2,459
Málaga	-17.74	-14.6	1,404	1,416
Sevilla	-17.34	-14.6	1,643	1,715
Valencia	-21.03	-15.4	1,187	1,317
Zaragoza	-19.59	-16.5	1,626	1,517
TOTAL	**-19.42**	**-16.4**	**2,072**	**2,141**

Sources: INE (Spanish Statistical Office), Department of Public Works and proprietary data.

Table A2 Price Setting Models (1-Thousand Threshold)

	Model 1 Coef./se	Model 2 Coef./se	Model 3 Coef./se
Listed at 1-thousand threshold	1.268***	0.827***	1.037***
Time dummies	YES	YES	YES
Location dummies	YES	YES	YES
Appraisal price	NO	YES	NO
Individual characteristics	NO	NO	YES
N	3,307	3,307	3,307
R-squared	0.27	0.28	0.28

Note: Each column corresponds to a model in which the dependent variable is price cut. In all cases, dwelling characteristics are the explanatory variables. Monthly time dummies identify the month in which the dwelling was sold. Postal code location dummies identify the location of the dwelling sold. Model 1 is the baseline model. Model 2 also includes the appraisal price as an explanatory variable. Model 3 adds to the individual characteristics of Model 1. Errors are clustered at the province level. Significance: *** p<0.01, ** p<0.05, and * p<0.1