List Price Information in the Negotiation of Commercial Real Estate Transactions: Is Silence Golden?

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Abstract

We examine the use (and non-use) of list price information in the process of marketing commercial real estate. While housing market research suggests that list prices can serve as a strong anchor and/or signal, list price information is included in less than one-third of the commercial property sales and is less likely to be included as part of the sellers' offering information for larger and more complex properties. Given the potentially powerful effect of list prices (first offers) on outcomes, the non-use of list price information is a puzzle. We speculate that the limited use of list prices may be due to the sellers' interests in both maintaining their informational advantage and not truncating higher than expected offers, especially during periods of economic growth or with more complex properties. Using a two-stage selection correction model, we find that office properties which provide list price information are, on average, associated with lower price outcomes (ceteris paribus) and that these outcomes vary by price cohort and economic condition. It is important to note, however, that while these findings identify a correlation, they do not necessarily imply causation. Our results support the notion that asymmetric information and information signaling play a dominant role in explaining the sellers' strategic non-use of list price information in the commercial real estate market and that the signaling effect is more pronounced in higher priced properties and during periods of strong economic growth.

Keywords : commercial real estate sales, negotiation, list price, asking price, anchoring, asymmetric information, signaling

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Introduction

While the process of negotiating real property transactions has received some attention in the literature, it remains poorly understood. It is clear that property-, market-, and transaction-specific information are critical to the process of establishing buyer offer prices. However, it is also well known that cognitive reasoning and human behavior can, and do, influence the processing of this information and decision making outcomes.

Past studies have examined the influence that revealed asking prices of sellers (the sellers' list prices) may have on the negotiation process and transaction prices.[1] This line of research has focused on the housing market. Less understood, however, is the use (or non-use) of list price information in the sale of commercial real estate, such as office buildings, retail centers, storage facilities and apartment complexes. Unlike in the housing market, income-producing commercial properties are often offered for sale without specifying the seller's list price.

The housing market research literature indicates that asking prices can play a strategic role in the transaction process.[2] Consistent with the anchoring heuristic, stating a high list price relative to market value has been found to be positively associated with a higher transaction price. In contrast, unusually high (or low) list prices may serve as a signal that conveys information to potential buyers about the sellers' motivations and/or atypical property features.

Given the possible strategic influence of anchoring and signaling, why sellers of commercial properties do not always use list price information to "anchor" a property's value and/or convey information is a puzzle. This paper contributes to the literature by (1) examining

[1] List prices and asking prices are used interchangeably in this paper.
[2] See, for example, Scott and Lizieri (2012); Bucchianeri and Minson (2012); Knight (2002); Yavas and Yang(1995); Knight etal. (1994); Horowitz (1992); Geltneretal. (1991); and Northcraft and Neale (1987).

the underlying determinants of the use of list prices and (2) evaluating the relationship between the use of list price information and subsequent transaction prices. We are not aware of any previous work that has looked at these issues within the context of the commercial property market.

We report that larger, more complex, and multi-tenant properties are less likely to reveal list price information. After controlling for property- and market-specific factors, the prices of properties sold that used list prices are, on average, lower than those sold without list prices. These price differences vary by price cohort and economic condition. Our findings do not imply that list prices cause transaction prices to be lower, but that their use is correlated with lower prices. The results support the notion that sellers do not reveal list price information in order to maintain an information advantage and to avoid truncating higher than expected offers, especially during periods of growth or when marketing complex properties. In this environment, revealed list prices may be effectively used to signal additional information (e.g., seller motivations) to the market. Thus, asymmetric information and signaling are argued to play a dominant role in explaining the sellers' strategic nonuse of list price information in the commercial property market.

The paper is organized as follows. The next section provides context and motivation for the study. The empirical methodology adopted is discussed in Section 3. The data are described in Section 4 and the test results reported in the "Empirical Results" Section, followed by the Conclusion.

Motivation and Literature

Much like in the residential market, the marketing and sale of commercial property is often facilitated by listing brokers and agents. The commercial property broker assembles information deemed relevant to potential buyers in forming and submitting offers for purchase. The materials assembled (e.g., an offering memorandum) typically include information on the market, the site and its location, the structure and other improvements, the tenants and their leases, comparable properties, and income and expense (pro forma) data. This information may be distributed directly to potential buyers and their advisors, or to potential buyers through the agents' network and their listing channels.

Compared to the housing market, commercial real estate tends to be marketed more directly to buyers and their advisors through the brokers' network. This effort may include placing the information on an online service such as LoopNet,[3] the Commercial Investment Multiple Listings Service (CIMLS), COMMREX Commercial Real Estate Exchange, and/or on a private password-protected website. Sometimes, especially for Class A properties, offering memoranda are sent directly to potential buyers, advisors, and agents indicating the bid due dates. As specified in the memoranda, the offers received may be accepted, negotiated, re-bid, or rejected.[4] In all cases, the information provided may or may not specify a seller's asking price.[5] Instead, some information regarding the seller's asking price may be privately conveyed during the process by what is commonly known as a "whisper" price (e.g., "we think the property should sell between x and y" or "we believe the property should sell at a cap rate of about z"). Thus, seller list prices are most often not openly revealed when transacting commercial property.

[3] In April of 2011, CoStar Group, Inc. announced that it was acquiring LoopNet, Inc. After a series of regulatory reviews, the transaction was completed on April 30, 2012 establishing a combined online commercial real estate data, analytics, and marketing resource.

[4] For example, the memorandum may indicate that "all interested parties must submit a non-binding Letter of Intent, by" a specified date. Generally, summarized information sheets known as "teaser" sheets or executive summaries are distributed to potential buyers through the brokers' network prior to sending formal offering memoranda with required bid dates.

[5] The offering may specify a list price, it may specify that the owner has not established a listing price, or it may omit any mention of list price information. Additional information, direct and indirect, may be provided in the listing that indicates possible seller motivations.

This approach is puzzling, because related research in the housing literature indicates that list prices may be strategically used to market the property. In looking at the housing market, Bucchianeri and Minson (2012) report that "the commonly recommended practice of underpricing in fact relates to less favorable outcomes... [and that] relatively high listing prices lead to higher sale prices." Specifically, list prices may serve as a price "anchor" and influence buyer perceptions of value.

The experimental research literature has looked at the effect of judgmental heuristics, the mental shortcuts or rules-of-thumb used by individuals in making decisions which may lead to inaccurate or biased conclusions. One heuristic identified is "anchoring" (Slovic and Lichtenstein 1971; Tversky and Kahneman 1974). In anchoring, an individual's estimate is unduly influenced by a reference value (i.e., anchor) where the adjustments from the reference are underweighted resulting in bias. Evidence of anchoring behavior has been found in a wide variety of conditions, including even when the anchor is unrealistic (Strack and Mussweiler 1997) and when the decision makers are warned (Wilson and Houston 1996). Particularly robust evidence of anchoring has been found in consumer behavior. Ariely et al. (2003), for example, find that the values placed on familiar products are strongly influenced by arbitrary anchors.[6]

Perhaps most relevant to this study, Northcraft and Neale (1987) indicate that when asked to value a single-family home, real estate agents (experts) were influenced by its list price (the reference anchor). Agents were provided an information packet and each asked to value the same home. All agents received identical information packets, except for the asking price of the subject property. Although most claimed the asking price was not relevant information, the agents' subsequent estimates of value were found to be positively correlated with the asking

[6] Davis and Holt (1993); Roth (1995); Gilovich et al. (2002); Camerer and Loewenstein (2004); and Furnham and Boo (2011) represent an outstanding collection of reviews of the experimental research literature.

price. Scott and Lizieri (2012) also find that individuals rely on anchors when estimating property values, even in the presence of significant incentives for accurate judgment, and that this influence can affect subsequent estimates. Consistent with an anchoring effect of the list prices, Black and Diaz (1996) report that in a controlled lab experiment both the buyers' opening offers and the eventual outcomes were positively correlated with manipulated list prices. They report that even when the manipulated list price is incongruous, negotiators may anchor on list price and devalue complex property- and market-specific information.[7] Finally, list prices may be viewed as first offers which have been shown to have powerful effects on outcomes (e.g., Van Poucke and Buelens (2002), Galinsky and Mussweiler (2001)).

Alternatively, sellers may use list prices to convey private information, as strategic signals, to specific buyers (e.g., Yavas and Yang 1995). For example, the list price may be set unusually low to signal a distressed sale, or unusually high to signal the seller's willingness to wait for a certain type buyer. In this case, perceived underpricing and over-pricing outcomes may be viewed as rational. Thus, list prices may be used by sellers strategically as anchors or as signals, or as both.[8] So why are list prices not consistently used in marketing commercial property?

One possible explanation is that commercial real estate investors, especially institutional investors, are sophisticated and experienced enough not to be significantly influenced by the list price. Investor offer prices are based primarily on the perceived income generating characteristics of the property and their own investment requirements. Viewed from this perspective, list prices are irrelevant and should have little if any anchoring effect on the sale

[7] Related to this line of research, Kamis et al. (2004) find that final bids are influenced by the seller reference prices (reserve price) in their experimental research evaluating auction processes.
[8] Additionally, bargaining outcomes may be influenced by the use of intermediaries (e.g., agents), their reputations and their incentives (see, for example, Myerson and Satterthwaite (1983); Bazerman et al. (1992); Croson and Mnookin (1997) and Yavas et al. (2001)).

prices of commercial properties. Ling et al. (2012) examine the potential effects of search costs and anchoring on transaction prices of commercial properties. They find little evidence that distant buyers and sellers anchor reservation prices on values in their local (home) markets. However, Bokhari and Geltner (2011) in a study focused on risk aversion, report a large anchoring or signaling effect (they cannot distinguish the type) associated with the overpricing of commercial property. Moreover, they find this effect is larger for more experienced or sophisticated investors. To the degree that this outcome can be attributed to anchoring, and not signaling, it challenges the notion that experts are less influenced by the anchoring heuristic.

A second possible explanation is that uncertain and asymmetric information may affect the propensity of making the first offer in a negotiation process (Oesch and Galinsky (2011)). In a commercial property sale, the seller typically holds more information than the buyer. Because of this, buyer offers span a larger range of possible values. By not disclosing a list price, the seller does not truncate the distribution of possible offers and is able to take advantage of those that might be higher than expected. If buyers happen to be aggressive they may exceed sellers' expectations and money is not "left on the table," consistent with the notion of "not tipping your hand." In this case, we would expect to see the use of list prices correlated with information certainty and the distribution of possible offers.

Alternatively, list price information may serve as an effective guide (and anchor) when the expected cash flows reflected in the pro forma are more uncertain, as with complex multi-tenant or low occupancy properties.[9] In this case, we would expect to see list prices associated more with larger, more complex properties (i.e., information uncertainty) and less so with smaller single tenant properties.

[9] Note that the occupancy information in the data examined is not consistently coded. Vacant and very low occupancy buildings, when identified, were removed from the analysis.

Third, the use (and non-use) of list prices may serve as a signal to potential buyers. List prices, when used, may convey (i.e., signal) information about the quality or type of the property to specific buyers, or about the willingness of the seller to negotiate. For example, a particularly low list price on a property may imply the seller is highly motivated and willing to negotiate, or that atypical property features exist (e.g., deferred maintenance, unusually low occupancy rates, or a number of other factors).

Or, finally, some combination of these explanations is possible. For example, the use of a "whisper price" may be viewed as a combination approach. It allows the seller to gage buyer response and solicit potential offer information, with the option of providing an anchor. Interestingly, Valley et al. (1992), studying the impact of information shared with third-party real estate agents in the housing market, discovered that transaction prices are higher when buyer reservation prices are shared with agents and lower when agents know only seller reservation prices.

Methodology

To evaluate the use and effect of list prices in commercial property transactions, we first examine the determinants of the likelihood of the seller using a list price when marketing the property, and then examine the effect of the list price on the sale price.

The Likelihood of Using a List Price

The likelihood of a list price being used when marketing the property is assumed to be a function of property characteristics, market characteristics, and sale conditions (i.e., seller, buyer, and sale conditions). The probability of using a list price can be estimated as a probit model, and specified as

$$Pr\left(LIST_{jt} = 1 | Z_{jt}\right) = \Phi\left(\beta_j Z_{jt}\right) + e_{jt} \qquad (1)$$

where $LIST_{jt} = 1$ if property j uses a listing price, 0 otherwise and Z is a vector of market, property, and sale condition variables at time t. Φ is the standard cumulative normal distribution, β_j the estimated coefficient, and e_{jt} the estimation error. $\left(\beta_j Z_{jt}\right)$ produces a probit score, or index, that is used to evaluate the marginal effect and statistical significance of each variable on the likelihood of including a list price as part of the offering.

Our hypothesis is that larger, more complex, property transactions are less likely to use listing prices in the transaction process. In complex transactions, the potential distribution of buyer offers may be wider, especially during times of strong economic growth. Because sellers retain the right to reject all offers, they may be less inclined to provide list price information (and reservation price information) that could truncate possible offers. In less complex smaller property transactions, where the potential distribution of offers is narrower, sellers are more likely to publish list price information in an effort to strategically “anchor” the potential offers, or to signal to prospective buyers their willingness to negotiate and (in the case of a unusually low listing price) sell at a “bargain.”

The Relationship between Using a List Price and the Transaction Price

We next examine the effect of a list price on sale price using a standard hedonic regression, specified as

$$\ln SP_{it} = a_0 + \sum_{j=1}^{k} \beta_j X_{jit} + c\, LIST_{it} + \sum_{t=1}^{T} \delta_t D_{it} + e_{it} \qquad (2)$$

where SP_{it} is the transaction price of property i at time t,; β_j is a vector of coefficients on property, condition of sale, and market characteristics, X_{jit};c is the coefficient on the dummy $LIST_{it}$ with values 1 if a list price is used in period t and 0 otherwise; δ_t the time coefficients of

D_{it}, time dummies with values of 1 if the ith property sold in period t and 0 otherwise; and e_{it} is the random error with mean, 0, and variance δ. Estimates of the coefficient, c, yield an estimate of the marginal relationship between the use of a listing price and the sale price of the property evaluated at the mean.

If list prices primarily serve as a "signal" to commercial property buyers of the sellers' willingness to negotiate the property sale, the estimated coefficient on *LIST* is expected to be negative. Alternatively, if commercial property list prices primarily (and effectively) serve as a strategic pricing "anchor," we would expect the estimated coefficient, c, to be positive. Of course, it is possible (and likely) that use of list price information is a combination of the two tactics. The influence of list price information on transaction outcomes will therefore depend on which effect dominates.

A Selection-Corrected Model—The Decision to List and the Transaction Price

Because a property's transaction price, SP_{it}, is likely to be affected by many of the same factors influencing the likelihood of using a list price in marketing the property, we estimate a two-stage model and examine alternate interactive specifications. We are interested in the estimated coefficient, c, on $LIST$; however, estimates of the OLS regression (2) may be subject to selection bias.

In the standard selection bias problem, information on the dependent variable for part of the sample is missing (or cannot be determined). In a second type of selection bias problem, dependent variable information is not missing, but its distribution is selective. In our case, the decision of sellers to use list price information may be selective. If we estimate an OLS regression with SP_{it} as dependent variable and a dummy variable indicating whether or not a list price is used, we may get a biased estimate on the correlation of using list price information because the distribution of transaction prices over the categories of properties using list prices ($LIST = 1$) and properties not using list prices ($LIST = 0$), are not random. That is, properties marketed with list prices may simply be different from those that do not use list prices. If these omitted characteristics are related to price, the estimated coefficient on $LIST$ may capture these effects and be biased.

To correct for this potential bias we adopt the Heckman selection correction procedure. The first step of the procedure is to estimate the probit regression (1) and then to include the inverse Mills ratio (IMR) created from the probit results as an independent variable in the second stage hedonic price Eq. (2), such that:

$$\ln SP_{it} = a_0 + \sum_{j=1}^{k} \beta_j X_{jit} + c\, LIST_{it} + \sum_{t=1}^{T} \delta_t D_{it} + \gamma \mathrm{IM}R_{it} + e_{it} \quad (3)$$

Heckman (1979) shows that that the inclusion of IMR corrects for the bias of the coefficient estimates. We note that the standard errors of the coefficient are also biased and additional corrections are required.

Data

The data used in this study come from the CoStar group, a Washington D.C. based public company that maintains one of the largest and most comprehensive databases of commercial real estate information in the U.S. A complete set of property- and transaction-specific variables for each of the characteristics of interest, including the seller's list price if used, is available for the January 2006 to December 2011 period. Office property sale observations (45,662) were initially identified for the 24 largest Metropolitan Statistical Areas (MSAs) in the U.S. for the study period. This 6-year period spans a range of market conditions, including a period of especially strong growth followed by a rapid decline and then a slight increase in U.S. commercial real estate market transaction activity. This allows us to examine our hypotheses under varying economic conditions.

The data were restricted to single office buildings greater than 2,000 square feet; located on sites less than 25 acres; sold for $100,000 to $500 million (with assessed values greater than $1,000); and less than 100 years of age at their time of sale. This initial filter resulted in a set of 33,022 observations. Effort was taken to include all viable building transactions; however, 9,893 sale observations identified as being sold as part of a more complex transaction (e.g., portfolio and multi-property sales, land sales, build-to-suit, non-arm's length sales associated with development or expansions) and 3,506 other atypical sales were excluded.[10] Thus, the final data set includes 19,623 office building transactions located in 24 U.S. metropolitan markets: Atlanta, Boston, Chicago, Dallas-Ft. Worth, Detroit, Denver, East Bay-Oakland, Inland Empire (California), Las Vegas, Los Angeles, New York, Orange (California), Orlando, Philadelphia, Phoenix, Portland, Sacramento, San Diego, San Francisco, Seattle-Puget Sound, South Florida, South Bay-San Jose, Tampa-St. Petersburg, and Washington D.C. A total the 238 office submarkets are identified within the 24 metropolitan markets.[11]

The observation variables are defined in Table 1 and their descriptive statistics reported in Table 2. Summary statistics (i.e., mean, median, min., max., and std. dev.) are reported for

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[10] The atypical sales such as 1031 tax-deferred exchanges, tenant purchases, distressed sales, sale lease-backs, or property shell sales, which are coded by CoStar as "detrimental condition" sales, represented approximately 7.7 % of the sales initially identified. Readers may be interested in noting that these observations were included in an earlier version of the paper. Their inclusion did not materially change the general results reported here when control variables were included in model estimates.

[11] CoStar identifies 354 broker-defined office submarkets having transaction activity within the 24 metro-politan areas examined. The number of the submarkets in the metropolitan areas varies from two in Inland- Empire (California) to 39 in South Florida. Over 30 % of the submarkets reported less than 10 transactions during the study period. To maintain transaction activity within the submarkets and across the periods, submarkets with less than 25 transactions were identified and grouped with a larger submarket. Submarkets were grouped using the following criteria: (1) they were adjacent to each other; (2) their transaction prices per square foot were similar; and (3) they were located at similar distances from the metropolitan area's central business district. This process resulted in the identification of 238 submarkets.

each of the non-dichotomous variables in Panel A and the frequencies (i.e., mean values) of the dichotomous variables reported in Panel B. To allow comparison we report the statistics for entire set of sale observations (ALL), as well as the set of observations that reported a list price (*LIST = 1*) in marketing the property, and the set of observations that did not use a list price (*LIST* = *0).*

Transaction prices range widely from a low of $100,000 to a high of $498 million, with a mean price of $6.4 million and a median price of $1.25 million, characteristic of a skewed price distribution. The average office observation is 31,050 square feet in size located on a 1.5 acre lot and 30.2 years old. The mean (median) price per square foot is $189.56 ($159.33). Assessed value of the properties average $3.59 million, or 55.9 % of the mean transaction price. Similarly, the median assessed value is 56.0 % of the median sale price. Of particular interest, only 30.8 % (6,042) of the sale observations report using a formal list price when marketing the property.

In Panel A, the observations sold using a listing price (*LIST* = 1) ranged from $100,000 to $385 million with a mean (median) sale price of approximately $2.2 million ($950,000). The average office property sold using a list price is 13,100 square feet, located on a 1.1 acre lot, 31.8 years old, and sold at a mean (median) price per square foot of $171.98 ($145.45). In comparison, the properties sold without using a list price (*LIST* = 0) ranged from $100,000 to $498 million, at a mean (median) price of $8.3 million ($1.4 million). Properties sold without a list price were, on average, 39,040 square feet located on 1.7 acre parcels and 29.5 years old. In addition, the mean (median) price per square foot of the *LIST* = 0 properties is $197.38 ($166.39). Thus, without controlling for general economic, local market, or individ-ual property factors, properties that use a list price when marketed for sale are, on average, descriptively smaller and lower priced (i.e., the median PSF for *LIST* =1 is $145.45 versus $166.39 for *LIST*-0).

The observations also vary considerably by building quality, tenant structure, and condition. For example, as reported in Panel B of Table 2, 6.2 % of the sale observations (ALL) are classified by Co Star as Class A (core, institutional-quality) properties, 67.8 % as multi-tenant properties, and 0.7 % are coded as “poor” quality properties. Of the sale observations that used list prices (*LIST*= 1), only 1.1 % are classified as Class A, compared to 8.5 % of the observations that did not use list prices (*LIST*=0); 64.7 % are multi-tenant properties compared to 69.2 %; and 0.9 % versus 0.6 % are coded as “poor” quality properties, respectively.

Sales vary by year in a pattern consistent with that casually observed during this period. In other words, strong transaction activity in 2006 and 2007 is followed by a precipitous decline in sale observations from 2008 to 2010, and then a slight increase in 2011. Observations sold in years 2006 through 2011 represent 22.8 %, 23.2 %, 18.2 %, 11.9 %, 10.9 % and 13.0 % of the data, respectively. Of those sold without using a list price, 52.7 % sold in 2006 and 2007, a period of very strong economic growth. In contrast, of those sold using a list price, 69.0 % sold during the 2008 to 2011 economic downturn and slow recovery. Also, noteworthy is the variation in observations by location, with approximately one-third (34.3 %) of the observations occurring within the five “gateway” cities of New York (13.2 %), Los Angeles (7.4 %), Chicago (6.2 %), Boston (4.2 %) and Washington, D.C. (3.3 %) and about two-thirds (65.7 %) occurring within the remaining 19 metropolitan markets.

As shown in Table 3, the percentage of properties marketed with a stated list price varies from a high of 38.5 % for properties $100,000 to $1 million, to a low of 3.2 % for properties in the $50 million to $100 million range. In general, higher priced properties were much less likely to be marketed with a formal listing price.

Empirical Results

Probit Model Estimates

The estimates of the probit model (Eq. 1) are reported in Table 4. Three general factors are examined: the characteristics of the structure, economic conditions, and conditions within the local market. To evaluate the sensitivity of the estimated coefficients, alternative specifications are estimated and the results for two specifications are reported. Model 4.1 includes the structural characteristics of the property (i.e., *SQFT*, *AGE*, *PSFG*, *CL-A*, *MULT*, and *COND*) and the year dummies as fixed effects in the specification. *SQFT* and *AGE* control for differences in property size (square feet) and age (years), while *PSFG* (sale price per square foot specified as a categorical variable),[12] *CL-A* (Class A property) and *COND* (poor quality of building condition) control for variations in property quality, and *MULT* is included to capture the variation in cash flow projection complexities associated with multiple- versus single-tenant properties. Each of the estimated coefficients has the expected sign and is statistically significant at the 1 % level, with the exception of *MULT* which is significant at the 5 % level and *COND* ($p = 0.116$). The results indicate that, on average, listing price information is less likely to be used on larger, newer, higher-quality, multi-tenant properties. This is consistent with the idea that the sellers of larger, more complex, income-producing office properties (with complex lease structures and

[12] Construction quality is included in the probit model as a factor related to the use of a listing price. Price per square foot, *PSF*, can serve as a proxy for construction quality. However, including *PSF* in the first stage probit estimates of two-stage selection correction models (presented in "Selection-Corrected Model Estimates") when the second stage includes both *SQFT* and *lnSP* causes potential problems with convergence the estimation results. To avoid this, price per square foot is specified as a categorical variable, *PSFG*, with values ranging from 1 to 12 (low to high) in all of the models estimated. *PSFG* is constructed to include approximately an equal number of observations in each category.

varying cash flow expectations) do not reveal list price information in order to maintain an information advantage and not constrain potential buyer offers.

The likelihood of using list price information is found to vary by year and by market. Observations sold in *YR11* are omitted and the estimates evaluated relative to that year. Interestingly, list prices were much less likely to be used during the strong economic period of 2006 and, *ceteris paribus*, a period of potentially large offer price variation. Model 4.2 includes location dummies to control for varying conditions across the markets. Market conditions also appear to affect the use of list price information, perhaps due to local economic conditions or local market norms. Coefficient estimates are reported for the five gateway cities of the 24 markets included. Relative to the omitted market area of Inland Empire, CA, list prices were more likely to be used in *L.A.*[13] The coefficient estimates for the other markets reported, *NYC*, *CHI*, *DC*, and *BOS*, are not statistically different from zero. It is also noted that the coefficient estimates on the structural or time variables reported in model 4.2 in Table 4 are not significantly different (statistically) from those reported in model 4.1 in Table 4.[14]

The marginal effects estimates for model specification 4.2 are also reported in right-hand column of Table 4. The estimated coefficient in the probit model represents the change in the probit index resulting from a one-unit increase in the independent variable. The marginal effects reported in the last column of Table 4 indicate the change in the probability of using list price information associated with a one-unit change in the independent variables, if dichotomous, and

[13] Inland Empire, commonly defined as the Riverside-San Bernardino-Ontario MSA, is located east of the Los Angeles MSA.

[14] The set of independent variables available for 4.1 and 4.2 are limited and additional property and seller characteristics (observed and unobserved) are likely to be important. To explore the potential significance of omitted property variables, unrelated to the time of sale, a subset of properties that sold twice is identified (1,849 obs.) and Model 4.2 re-estimated to include the variable (*LIST1*), where *LIST1* is 1 if a listing price was used on the property's previous sale, else 0. The estimated coefficient on *LIST1* is not significantly different from zero at the 10 % level (β = 0.149; t = 1.61). This reinforces the explanatory strength of the limited set of factors included in 4.2. However, additional work is needed to investigate the role of the seller, broker, and other potentially important time varying characteristics on the use of list prices.

a one standard deviation change in the independent variable evaluated at its mean value, if non-dichotomous. Thus, a one standard deviation increase in the size of the structure (*SQFT*) is correlated with a 13.3 % decline in the probably of using a stated list price in marketing the property (or an increase of 79,890 square feet infers a 13.3 % decline in the probability). Similarly, a one standard deviation increase (25.4 years) in the property's age increases the probability by approximately than 1.2 %. The quality and complexity of the property are important factors in determining the probability of using a list price. For example, a one-unit increase in PSF category and the marketing of Class A (*CL-A*) and multi-tenant (*MULT*) properties decreases the likelihood by 0.6 %, 12.7 % and 1.3 %, respectively. Properties sold as coded in poor condition (*COND*) are 5.7 % more likely to be sold using a list price. Finally, properties sold in 2006 during the real estate boom, controlling for structural and local market factors, were approximately one-third less likely to be marketed using a list price than in the other years of the study.

OLS Regression Estimates

To examine the correlation that providing seller list price information has (if any) with transaction prices, we first estimate a standard hedonic regression. This will be used as a benchmark to compare to the alternative two-stage selection-corrected estimates presented in "Selection-Corrected Model Estimates". Table 5 reports the OLS estimation results from Eq. (2) where structure, sale year and market factors are regressed on the natural logarithm of sale price, *lnSP*.[15] The results from alternative models are presented to examine the sensitivity of the

[15] This model specification pools the observations in estimating the factor coefficients and in doing so it implicitly assumes that the estimated coefficient on each variable is constant across each of the other model factors (i.e., varying structure characteristics, time and markets). This is an important limitation of the model. Unfortunately, sufficient data are not available to reliably estimate cross-sectional results across each of the 24 markets for each

estimated coefficients to the specification. Model 5.1 includes as explanatory variables the structural characteristics, a vector of time dummies indicating the year sold, a vector of metropolitan and submarket location dummies, and a dummy (*LIST*) indicating if the observation included a list price when marketed. Model 5.2 adds to 5.1 the interaction of *LIST* with the time dummies to evaluate any change in the estimated coefficient on *LIST* across time.

The set of structure, time and market variables in Model 5.1 explains 73.6 % of the variation in transaction prices (adj-R2 = 0.736). The coefficient estimates and the overall explanatory power of the model are not significantly affected when *LIST* is interacted with the time dummies in Model 5.2. Clearly the explanatory power of the basic hedonic model, Model 5.1, is largely dependent on *SQFT* (t-stat = 90.12), LOT (t-stat = 31.09), and the quality of the property variables, *AGE*, *CL-A*, *MULT*, and *COND*. The estimated coefficient on *SQFT*, 0.016, indicates that on average a 1.6 % change in the price occurs relative to a 1-unit (1,000 sq.ft.) change in *SQFT* evaluated at the mean price. Thus, a one square foot change at the mean price of $6.42 million represents a price per square increase of $102.72 [(6.42 million × 0.016)/1000], indicating an estimated marginal price per square foot well within the bounds of the norm for this time period for standard non-class A property improvements excluding land. In addition, the estimated coefficient on $SQFT^2$ indicates that prices increase at a decreasing rate relative to size, consistent with expectations. Evaluated at the mean, one-unit (1,000 sq.ft.) change in the size of the land, *LOT*, increases the transaction price by 0.17 %, or $10,920 at the mean sale price.[16] The estimated coefficient on *AGE* is significant (and negative). The relatively small effect of aging (−0.4 % per year) compared to that seen in housing may be due to the higher construction

period. To evaluate the sensitivity of *LIST* across varying economic conditions and structural cohorts, LIST (the key variable of interest) is interacted with the other variables of interest.

[16] The marginal price of land ($10.92/sf) and the marginal price of the property ($113.64/sf), translate to a land-to-property price ratio of approximately 24.1 % assuming a floor area ratio (FAR) of 0.334 constructed from the median floor size and median land area (8.15/24.39).

standards of commercial properties coupled with more frequent renovations.[17] Finally, the estimated coefficients on the Class A property (*CL-A*) and multi-tenant property (*MULT*) dummies indicate these properties are transacted, on average, at prices 31.8 % and 22.9 % greater than other properties of similar size and age. This is likely due to their higher-quality and site-specific location characteristics. Properties identified as “poor” quality (*COND*) sold, on average, at prices 20.2 % less than similar properties, holding constant the other factors identified.

The estimated coefficients on the year dummies in 5.1 are evaluated relative to 2011, the omitted year. It is interesting to note that these coefficient estimates suggest market price movements similar to independent commercial property price index measures (e.g., Moody’s/RCA CPPI). Differences in the coefficient estimates indicate slight price increases in prices from 2006 to 2007 followed by dramatic price declines from 2007 to 2009, follow by a price leveling or small price increases from 2009 to 2010.[18] In addition, estimates indicate substantial price variation in the properties sold associated with market location.

Of particular interest is the estimated coefficient on *LIST*. The estimated coefficient, c, is found to be negative and significant. Controlling for property, time, and market differences, properties that reveal list price information sold, on average, at prices 9.8 % less than properties marketed without list price information. This correlation is not interpreted as causal. To the degree that we are able to control for property quality in this model, this relationship suggests that list price information may serve more to “signal” to buyers specific sale conditions and the sellers’ willingness to negotiate, and serve less as a behavior pricing “anchor” within the

[17] In a meta analysis that looks at hedonic house price estimates, Sirmans et al. (2006) report that the estimated coefficient on age is −8.9 % for housing and that it can vary by as much as 1.4 % across regions.
[18] Moody’s/RCA CPPI estimates that the annual price change for U.S. office properties were −19.2 %, −31.7 %, respectively, from December 2007 to December 2009.

negotiations.[19] However, the two effects cannot be considered independently. Thus, the degree of the anchoring behavior (if any) cannot be evaluated separate from the signaling effect.

To evaluate the potential variation in the estimated coefficient of *LIST* across time, Model 5.2 interacts *LIST* with the time dummies, *YRt*, where *t* is the year sold. The estimated coefficient on each cross product, *LIST*YRt*, represents the marginal change in the estimated coefficient of *LIST* associated with year *t*. In this specification, the estimated coefficients of *LIST* and *LIST*YRt* are considered jointly to interpret the relationship between the use of a list price and the selling price of the property. The coefficients on *LIST* and *LIST*YRt* reported for 5.2 in Table 5 indicate that properties using list prices sold, on average, at prices 9.1 % (i.e., −17.9 % + 8.8 %) to 13.3 % (i.e., −17.9 % + 4.6 %) less than properties marketed without list prices in all years except 2009. In 2009, the trough of the Great Recession, the coefficient on the cross product *LIST*YR09* is estimated to be 0.243 ($p < 0.01$) resulting in an estimated combined effect of +6.4 %. However, because the standard error of the interacted coefficient *LIST*YR09* is 0.042, the combined effect is not statistically different from zero. This suggests that during an especially weak economic period, such as 2009, the use of list prices is associated with substantially less of a sale price decrease (i.e., the "signaling" effect is weakened).

Coefficient estimates using an alternate hedonic specification (Models 5.3 and 5.4) are also reported in Table 5. In this specification, the property characteristic variables discussed are replaced by estimates of the property's assessed value (*AV*) from the year prior to its sale. This specification assumes that the assessed values capture the "true" value variations of the

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[19] Unfortunately, because commercial properties are often marketed directly to buyers and their advisors through the brokers' network (sometimes using a bid request process), reliable time-on-market (TOM) information is not available. We suspect that the signaling is likely correlated (negatively) with TOM, but we are not able to control for this factor. In addition, information regarding specific lease terms and property occupancy rates in the dataset is not consistently reported. Observations with very low occupancy rates, if reported, have not been included in the analysis.

properties. Because income property values are a function of income expectations and return requirements (information which is generally not publicly available), hedonic specifications using solely physical characteristics may not adequately explain income property values. Assessed values, often constructed using owner-provided property-specific income information and derived market discount rates, are likely to represent a valid explanatory variable for explaining income property values.[20]

Focusing our discussion on Model 5.3, this specification explains 78.0 % of the variation in prices. This is very similar to the explanatory power of the standard hedonic specification, Model 5.1 (adj-R2 = 73.6 %), that includes an identical set of control variables for economic and market conditions. The estimated coefficients on the year dummies suggest a price movement profile similar to that reported for 5.1 and 5.2 that is generally consistent with independent indices and casual market observations. In Model 5.4 the interaction terms are added and a similar profile of coefficients estimated. Evaluating the estimated coefficients of the interaction terms indicates that the marginal effect of *LIST* is associated with lower sale prices during stronger economic periods (e.g., 2006 and 2007) and that this relationship is substantially dampened during weaker economic periods (e.g., 2009). In all periods the combined effect is negative, including 2009 where the effect is −1.05 % (−19.9 % + 18.4 %). Finally, as expected, the estimated coefficients on the market dummies change substantially in response to differences in the assessed value measures across the markets. In general, the coefficient estimates for Models 5.3 and 5.4 are consistent with those reported for 5.1 and 5.2, the standard hedonic

[20] See, for example, Clapp and Giaccotto (1992) and Gatzlaff and Holmes (2012). To be representative, appraised values do not need to be reported at the property's full (100 %) market value. The effects from the differences in market conventions (e.g., proportional values schemes) can controlled by including market area dummies within the regression model. However, the values within each market are assumed to be vertically and horizontally efficient.

model. Because of their model identification characteristics, 5.3 and 5.4 are used as the second stage specification in the selection-corrected model presented in the next section.

Selection-Corrected Model Estimates

Given the results of the probit model (Table 4), it is likely that *LIST* is selective. In other words, the price distribution on the types of properties whose sellers elect to use or not use list price information in the transaction process are most likely non-random. To control for the likelihood of heterogeneity selection bias in the *LIST* variable, a two-stage Heckman selection-corrected model is estimated.

The selection-corrected model uses the probit specification from Model 4.2 to estimate the first stage and construct the inverse Mill's ratio (*IMR*). The second stage is estimated by including the *IMR* in the model 5.3 and 5.4 specification.[21] The results of the second stage estimates of the selection-corrected model are reported in Table 6. With the exception of the inclusion of the *IMR*, the second stage specification of Model 6.1 is identical to Model 5.3. To evaluate the effect of any selection bias on the coefficient estimates, the estimation results from 6.1 are compared with that of OLS model specification 5.3. The estimated coefficient (γ) on *IMR* reported for Model 6.1 is statistically significant at a 1 % level (t-stat = 13.05). Thus, the hypothesis of no selectivity is rejected.

Focusing on Model 6.1 we note that the explanatory power of the alternative specifications are similar (Model 6.1 adj-R2 = 78.2 % versus Model 5.3 adj-R2 = 78.0 %). In general, the coefficient estimates of the selection-corrected model estimates reinforce the results reported earlier. The estimated coefficients on *lnAV* (β = 0.698 vs. 0.705) are nearly identical. While the estimated coefficients on the year dummies change, which is to be expected if the use

[21] The standard errors in the selection corrected model are adjusted and corrected t-stats reported.

of *LIST* varies by year, the differences *between* the coefficients for each subsequent year dummy (the annual appreciation rates) do not substantially change. Thus, the annual price movements reflected by the coefficients of the annual dummies are similar to those reported in the previous section. Finally, the estimated coefficients on market dummies are not substantially affected. Again, as in 5.1, the estimated coefficients of the market dummies reflect both the price and the assessed value variations across the markets.

Of particular interest is the estimated coefficient on *LIST*. In both the OLS (5.3) and the selection-corrected model (6.1), the estimated coefficient on *LIST* is significant ($p < 0.01$). The coefficient's magnitude in the selection-corrected model is dampened slightly ($c = -0.119$ in Model 6.1 versus $c = -0.126$ in Model 5.3); however, the effect of the selection-correction on the estimate is not dramatic. Both models suggest that the "signaling effect" of using a list price in marketing a property dominates a possible anchoring effect.

Interacting *LIST* with the year dummies (Model 6.2, *LIST*YRt*) indicates that the effect of *LIST* varies by year and appears to be related to the economic conditions. For example, in a period of strong economic contraction (e.g. 2009) the signaling effect is dampened by 15.8 % ($p < 0.01$). Evaluated at the mean, the signaling effect is reduced to only −1.1 % (−16.9 % + 15.8 %) during 2009—a combined estimate that is not statistically different from zero. In contrast, in a period of strong economic expansion (e.g., 2006) the negative effect on price is found to be magnified and the combined effect, −17.9 %, statistically different from zero. The estimated coefficient on the *LIST* related variables are consistent with the idea that stated list prices serve as a signal associated with lower sale prices and the effect is found to dominate possible list price anchoring effects.[22] Furthermore, the "signaling effect" (i.e., the sellers' ability to convey property and/or seller information through list prices) increases during periods of strong economic growth and decreases during periods of economic weakness.[23]

Finally, *LIST* is interacted with the assessed value, *lnAV*, and the estimation results are reported in Model 6.3 (selection-corrected). The estimated coefficient on *LIST***lnAV* is −0.067 and is significant at a 1 % confidence level. The negative coefficient indicates that as assessed values increase (i.e., property values appreciate), the transaction prices on properties using list price information increase at a decreased rate relative to properties sold without list prices. In other words, the signaling effect (i.e., the conveyance of property- or seller-specific information) increases with price. On average, the use of list prices is associated with a larger price reduction for higher price properties. Evaluated at the mean *lnAV* the use of a stated list price, *LIST*, in 2011 (the omitted year) is calculated to be associated with a 17.4 % (i.e., 0.717 + (−0.067 * 13.3047)) reduction in the price relative to others not marketed with a list price, *ceteris paribus*. This relative price decreases (increases) 0.067 % for every 1 % increase (decrease) in assessed value. At assessed values of $200,000, the use of *LIST* is estimated to be related to a 10.1 % decline in sale prices. Coupled with the positive coefficient estimate of 15.5 % on the 2009 interacted time dummy, this hints at the possibility of a dominant positive anchoring effect for some types of properties, especially during periods of economic weakness. Of course, the linear

[22] We should mention that alternative model specifications that included time-on-market information were estimated with very little change in the coefficients of interest. The availability of the time-on-market data is quite limited and its reliability questionable; hence, it has not been reported.

[23] Viewing the use of list prices, very broadly, as related to the use of reserves in auctions, these results are consistent with work in the auction literature. For example, Gan (2012) indicates that loss averse sellers will choose to set reserve prices (e.g., motivated sellers will choose to reveal list prices), and more sellers will prefer auctions without reserves when the market is hot (e.g., revealed list prices in a strong market provide clearer signals).

extrapolation of the estimated coefficients over such a wide value range is problematic. Therefore, the models are estimated by price cohort in the next section.

Model Estimates by Price Cohort and Select Markets

In “Selection-Corrected Model Estimates” we report that the magnitude of the list price signaling effect varies by price cohort. In this section we briefly examine the effect separately by price cohort and for select markets. We first look at two price cohorts: (1) properties transacted at prices between \$100,000 and \$10 million, and (2) properties transacted at prices between \$10 million and \$500 million.[24] Selection-correction models specified identical to Models 6.1 and 6.2 are estimated for each cohort and their results reported in Table 7. The estimation results for the lower-priced tier are reported in Models 7.1 and 7.2. In both cases, the estimated coefficient on *LIST* is substantially less than (<50 %) the identical model estimated using the entire pooled sample (e.g., Model 7.1 $c = -0.056$ versus Model 6.1 $c = -0.119$). Comparing the estimated coefficient of *LIST* in the selection corrected model, Model 7.2, shows a similar result (e.g., Model 7.2 $c = -0.062$ versus Model 6.2 $c = -0.169$). In Model 7.2 the results are consistent with 6.2 and 6.3 indicating that this correlation was magnified during periods of strong economic growth ($\beta = -0.077$, $p < 0.10$ for the estimated coefficient on *LIST*YR06*) and substantially dampened (i.e., effectively eliminated) during the 2009 economic contraction ($\beta = 0.086$, $p < .05$ for the estimated coefficient on *LIST*YR09).*

The coefficient on *LIST* estimated using the higher-priced cohort (\$10 million to \$500 million) and the standard OLS model (Model 7.3) is −0.147. Estimates using a selection

[24] The price cohorts are selected to generally represent the non-institutional (\$100,000–\$10 million) and institution (\$10 million to \$500 million) categories. To mitigate estimation bias segmenting the data by assessed value was evaluated. However, because assessed values as a percentage of their market values vary substantially by location, this was not employed. Other alternatives were considered but segmentation by the approximate non-institutional and institutional price cohorts was determined to be most meaningful to the reader.

correction model do not converge and could not be reported. However, based on the previous results reported, it is reasonable to suggest that the OLS estimate represents the upper bound of the coefficient estimate on *LIST*. Thus, consistent with earlier results, the signaling effect is found to differ by price cohort, by economic period and consistently dominates a possible anchoring effect.

Finally, we estimate model specifications 6.1 and 6.2 using data from each of the "gateway" markets to document the variation in the estimated coefficients on *LIST* across select markets.[25] The estimation results are reported in Table 8. Panel A of Table 8 reports the estimated coefficients on *LIST* for city-specific estimates consistent with model 6.1. Panel B reports the estimated coefficients on *LIST* and its interacted time dummies consistent with model 6.2. To facilitate comparison, the coefficients of interest that were estimated using the pooled sample for all 24 markets are reported as "benchmark" statistics in the right-hand column. The coefficient estimates reported in Panel A range from −0.069 in *LA* to −0.226 in *CHI*, compared to the benchmark of −0.119. The estimated coefficient in each market is negative and statistically different from zero. While the estimated coefficients on *LIST* vary across the four major markets, they are not statistically different (i.e., at $p < 0.05$) from each other. The standard errors of the city-specific *LIST* coefficient estimates range from 3.77 % to 6.70 %, compared to a standard error in the pooled sample estimate of 1.22 %. Thus, we are not able to indicate that the signaling effect varies significantly across these markets.

In Panel B the time-varying nature of the signaling effect is considered within the major markets. Here, the estimated coefficients on *LIST* are evaluated jointly with the estimated

[25] Results are reported for NYC, LA, CHI, and BOS. The transaction data were very limited in 2006 for DC and reliable estimates are not available.

coefficient on the interacted time-dummy. In general, the estimated coefficient on *LIST* is negative for each market, except in LA where it is not statistically different from zero. In addition, the estimated coefficients on the interaction terms in each period and in each market are not statistically different from zero, except for *LA* in 2007 ($p < 0.10$) and for *CHI* in 2009 ($p < 0.10$). While the coefficient estimates are sizable (relative to the estimated coefficient on *LIST*) and economically meaningful, they are estimated with substantial error.

The estimated coefficients from the pooled sample (*All 24 Mkts*) along with the price index generated from the time dummy coefficients estimated in model 6.2 are charted in Fig. 1. Graphically, we note that the signaling effect (a negative effect on transaction prices) is stronger during the 2006 period of economic growth and weaker during the economic downturn of 2009. This may suggest the signal of marketing a property using a list price is “clearer” during strong economic conditions. In addition, it should be noted that the time-varying signaling effects within the city-specific measures are charted and while measured with considerable error the estimated coefficients tend to follow a pattern similar to the pooled sample.

Conclusion

This study examines the use (and non-use) of list price information in the process of marketing income-producing office properties. While previous studies suggest that list prices in the housing market transaction process can serve as anchors and/or as signals, list prices are not generally stated as part of the standard commercial property listing. Given the powerful effect of first offers on outcomes, the non-use of list price information is a puzzle.

Our results indicate that list prices are less likely to be used when the transactions involve more complex properties with greater information asymmetries such as larger, multi-tenant, institutional-grade properties. We speculate that the limited use of list prices may be due to the sellers' interests in both maintaining their informational advantage and not truncating higher than expected offers, especially during periods of economic growth or with more complex properties.

Using a two-stage selection correction model, we find that commercial office properties that are marketed using list price information are, on average, associated with lower transaction prices. It is important to note, however, that this correlation does not imply causation. Rather, the finding is consistent with the notion that sellers use list price information to signal specific property sale conditions (e.g., tenant quality, lease terms) and/or a willingness (or unwillingness) to negotiate a rapid sale. Consistent with this, we find the signaling effect to be more pronounced for higher priced properties and less pronounced during times of weak economic growth. Our results indicate that the strategic use (and non-use) of list prices to signal seller motivations appears to dominate possible price anchoring effects that may accompany the use of revealed list prices in the transaction process.

This study represents one of the first studies to examine the use list prices in marketing commercial real estate. Additional work that looks at the factors influencing the decision to use list prices is important to resolving the question of the effect of list prices on outcomes.

Table 1. Variable definitions.

Variable	Definition
LIST	Dummy variable = 1 if seller uses a listing price, otherwise 0.
SP	Transaction price ($000 s).
lnSP	Natural log of the transaction price, *SP*.
AV	Assessed value ($000) in the most recent year prior to the sale.
lnAV	Natural log of the assessed value, *AV*.
SQFT	Building square footage (000 s).
AGE	Actual age of the building (years).
LOT	Land area square footage (000 s).
PSF	Actual price per square foot.
PSFG	Categorical variable of PSF, with values = 1 to 12 (low to high).
IMR	Inverse mills ratio generated by selection-corrected estimates.
CL-A	Dummy variable = 1 if class A office, otherwise 0.
COND	Dummy variable = 1 if classified in poor condition, otherwise 0.
MULT	Dummy variable = 1 if multi-tenancy structure, otherwise 0.
YR06 to YR11	Dummy variable = 1 if sold in respective year, otherwise 0.
NYC	Dummy variable = 1 if located in New York metropolitan area, otherwise 0.
LA	Dummy variable = 1 if located in Los Angeles market, otherwise 0.
CHI	Dummy variable = 1 if located in Chicago market, otherwise 0.
DC	Dummy variable = 1 if located in Washington D.C. market, otherwise 0.
BOS	Dummy variable = 1 if located in Boston market, otherwise 0.

This table provides a list of variable definitions. Property transactions in five U.S. “gateway” markets, New York, Los Angeles, Chicago, Washington, D.C. and Boston, are identified using dummy variables. In addition, dummy variables are included for 19 other U.S. markets and 238 office submarkets when estimating the models.

Table 2. Descriptive statistics.

Var	**Statistic**	***ALL 19,623 obs***	***LIST = 1 6,042 obs***	***LIST = 0 13,581 obs***
Panel A: non-dichotomous variables				
	Mean	6,423.59	2,183.67	8,309.88
	Med	1,250.00	950.00	1,425.00
SP	Min	100.00	100.00	100.00
	Max	498,000.00	385,000.00	498,000.00
	SD	23,825.22	9,138.72	27,775.66
	Mean	3,591.72	1,501.46	4,365.15
	Med	700.00	604.03	748.73
*AV**	Min	1.04	1.26	1.04
	Max	251,527.87	141,071.28	251,527.87
	SD	12,178.93	4,128.03	13,953.33
	Mean	31.05	13.10	39.04
	Med	8.15	6.30	9.81
SQFT	Min	2.00	2.00	2.00
	Max	1,429.80	1,173.64	1,429.80
	SD	79.89	29.92	92.83
	Mean	65.32	45.89	73.97
	Med	24.39	20.04	27.44
LOT	Min	1.00	1.00	1.00
	Max	985.33	933.93	985.33
	SD	110.68	81.14	120.53
	Mean	30.19	31.78	29.49
	Med	26.00	28.00	25.00
AGE	Min	0.00	0.00	0.00
	Max	100.00	100.00	100.00
	SD	25.40	25.49	25.33
	Mean	189.56	171.98	197.38
	Med	159.33	145.45	166.39
PSF	Min	1.82	5.30	1.82
	Max	2,168.02	2,168.02	2,116.86
	SD	141.02	120.91	148.44
	Mean	6.01	5.63	6.18
	Med	6.00	5.00	6.00
PSFG	Min	1.00	1.00	1.00
	Max	12.00	12.00	12.00

Var	**Statistic**	***ALL 19,623 obs***	***LIST = 1 6,042 obs***	***LIST = 0 13,581 obs***
	SD	3.08	2.94	3.12
Panel B: dichotomous variables				
CL-A	Freq	6.2 %	1.1 %	8.5 %
COND	Freq	0.7 %	0.9 %	0.6 %
MULT	Freq	67.8 %	64.7 %	69.2 %
YR06	Freq	22.8 %	5.5 %	30.5 %
YR07	Freq	23.2 %	25.5 %	22.2 %
YR08	Freq	18.2 %	22.5 %	16.2 %
YR09	Freq	11.9 %	14.4 %	10.8 %
YR10	Freq	10.9 %	13.9 %	9.6 %
YR11	Freq	13.0 %	18.2 %	10.7 %
NYC	Freq	13.2 %	11.2 %	14.2 %
LA	Freq	7.4 %	8.4 %	6.9 %
CHI	Freq	6.2 %	5.6 %	6.4 %
DC	Freq	3.3 %	2.1 %	3.8 %
BOS	Freq	4.2 %	3.6 %	4.4 %

This table provides descriptive statistics for the entire dataset (ALL), that contains 19,623 office property transactions in 24 U.S. markets, the subset of transactions that used LIST prices (LIST = 1), and the subset of transactions that did not use LIST prices (LIST = 0). The variable definitions are reported in Table 1. Panel A reports mean, median (Med), minimum (Min), maximum (Max) and standard deviation (SD) for non-dichotomous variables. Panel B reports frequency (Freq) statistics for dichotomous variables. The transaction price (SP), the assessed value (AV), the lot size (LOT), and the building size (SQFT) amounts are reported in 1,000 s.
**AV is limited to 15,884 obs.*

Table 3. Sale and list price frequency by price cohort.

Price cohort	No. of sale observations	% w/LIST information
0.1 M to 1 M	8,120	38.5 %
1 M to 5 M	8,036	31.0 %
5 M to 10 M	1,373	19.8 %
10 M to 50 M	1,682	8.3 %
50 M to 100 M	280	3.2 %
100 M to 500 M	224	4.0 %
All cohorts	19,623	30.8 %

Tables 4. Probit estimate of likelihood of list price used.

(Dep. Var. = *LIST*)

Independent variable	(4.1) β	(t-stat)	(4.2) β	(t-stat)	Marginal effect
Intercept	0.051	(1.42)	−0.020	(−0.28)	
SQFT	−0.005	(−15.40)***	−0.005	(−15.61)***	−0.133
AGE	0.001	(4.03)***	0.002	(3.90)***	0.012
PSFG	−0.024	(−7.07)***	−0.021	(−5.44)***	−0.006
CL-A	−0.425	(−5.79)***	−0.413	(−5.57)***	−0.127
MULT	−0.043	(−2.03)**	−0.043	(−2.01)**	−0.013
COND	0.177	(1.57)	0.186	(1.62)*	0.057
Economic conditions					
YR06	−1.219	(−31.57)***	−1.223	(−31.20)***	−0.375
YR07	−0.170	(−5.19)***	−0.178	(−5.35)***	−0.055
YR08	−0.108	(−3.21)***	−0.114	(−3.30)***	−0.035
YR09	−0.180	(−4.87)***	−0.180	(−4.81)***	−0.055
YR10	−0.118	(−3.11)***	−0.120	(−3.15)***	−0.037
Market conditions					
NYC			−0.083	(−1.20)	−0.025
LA			0.209	(2.84)***	0.064
CHI			0.023	(0.30)	0.007
DC			−0.061	(−0.68)	−0.019
BOS			−0.083	(−1.03)	−0.026
Coefficient estimates for 19 additional city-specific market dummies in each model are not reported.					
AIC	21,589		21,193		N.A.
Schwarz	21,684		21,469		N.A.
N	19,623		19,623		19,623

*This table reports the probit regression results from Eq. (1) on the likelihood that the seller will use a list price in marketing commercial real estate properties. The dependent variable is LIST, which equals 1 if the property sale uses a listing price and 0 otherwise. The definitions of the independent variables are listed in Table 1. The t-values are reported in parentheses. The ***, **, and * denote p < 0.01, p < 0.05, and p < 0.1 respectively. The last column "Marginal Effect" reports the marginal effect estimates from the probit regression model 4.2. The marginal effect estimates measure the conditional probability change in the likelihood that the seller will use a list price in marketing the properties produced by one standard deviation (for two non-dichotomous variables: SQFT and AGE) or one unit (for all dichotomous variables) change in each of the independent variables.*

Table 5. OLS regression estimates on the relationship between list and transaction price.

Independent variable	(OLS Dep. Var. = *lnSP*)							
	(5.1) *OLS* β (t-stat)		**(5.2) *OLS* β (t-stat)**		**(5.3) *OLS* β (t-stat)**		**(5.4) *OLS* β (t-stat)**	
Intercept	13.378	(305.19)***	13.416	(296.18)***	4.124	(59.99)***	4.158	(59.68)***
LIST	−0.098	(−8.35)***	−0.179	(−6.31)***	−0.126	(−10.20)***	−0.199	(−6.40)***
SQFT	0.016	(90.12)***	0.016	(90.16)***				
$SQFT^2$	−1.2E-05	(−61.66)***	−1.2E-05	(−61.71)***				
LOT	1.7E-03	(31.09)***	1.7E-03	(31.03)***				
AGE	−0.004	(−6.15)***	−0.004	(−6.23)***				
AGE^2	−0.8E-05	(−1.13)	0.8E-05	(−1.08)				
CL-A	0.318	(11.22)***	0.319	(11.25)***				
MULT	0.229	(20.60)***	0.229	(20.62)***				
COND	−0.202	(−3.30)***	−0.204	(−3.33)***				
lnAV					0.705	(179.29)***	0.705	(179.30)***
YR06	0.415	(22.87)***	0.380	(17.47)***	0.393	(20.60)***	0.365	(16.14)***
YR07	0.419	(23.82)***	0.388	(17.10)***	0.423	(22.63)***	0.400	(17.03)***
YR08	0.340	(18.43)***	0.318	(13.24)***	0.294	(15.10)***	0.253	(10.27)***
YR09	0.024	(1.17)	−0.072	(−2.76)***	−0.035	(−1.63)	−0.099	(−3.74)***
YR10	0.005	(0.23)	−0.034	(−1.24)	−0.040	(−1.77)*	−0.051	(−1.80)*
*LIST*YR06*			0.077	(1.56)			0.053	(1.03)
*LIST*YR07*			0.069	(1.92)*			0.054	(1.39)
*LIST*YR08*			0.046	(1.23)			0.110	(2.74)***
*LIST*YR09*			0.243	(5.90)***			0.184	(4.15)***
*LIST*YR10*			0.088	(2.10)**			0.024	(0.53)
NYC	0.310	(3.18)***	0.305	(3.14)***	0.098	(1.04)	0.094	(1.00)
LA	0.118	(0.81)	0.116	(0.80)	0.243	(1.81)*	0.134	(1.77)*

	(OLS Dep. Var. = *lnSP*)							
Independent variable	**(5.1) *OLS* β (t-stat)**		**(5.2) *OLS* β (t-stat)**		**(5.3) *OLS* β (t-stat)**		**(5.4) *OLS* β (t-stat)**	
CHI	−0.021	(−0.35)	−0.025	(−0.42)	0.967	(16.61)***	0.962	(16.54)***
DC	0.774	(7.18)***	0.770	(7.15)***	0.302	(2.89)**	0.298	(2.85)***
BOS	0.880	(11.04)***	0.884	(11.10)***	0.665	(8.49)***	0.665	(8.50)***
Coefficient estimates for 19 additional city-specific market dummies and 238 submarket dummies included in each model are not reported.								
Adj-R^2	0.736		0.736		0.780		0.780	
F	214		214		227		223	
N	19,623		19,623		15,884		15,884	

*This table reports the OLS regression estimates from Eq. (2) to examine the correlation that providing seller list price information has with commercial real estate transaction prices. The dependent variable is logarithm of sale price. The independent variables include building characteristics, sale year, and market factors. The definitions of the independent variables are listed in Table 1. The t-values are reported in parentheses. The ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$ respectively.*

Table 6. Two-stage selection-corrected regression estimates.

(Selection-corrected stage 1 Dep. Var. = *LIST*; stage 2 Dep. Var. = *lnSP*)						
Independent variable	**(6.1) Stage 2 selection-corrected β (t-stat)**		**(6.2) Stage 2 selection-corrected β (t-stat)**		**(6.3) Stage 2 selection-corrected β (t-stat)**	
Intercept	3.798	(52.16)***	3.822	(51.69)***	3.653	(47.79)***
LIST	−0.119	(−9.72)***	−0.169	(−5.45)***	0.717	(6.55)***
lnAV	0.698	(176.24)***	0.697	(176.20)***	0.709	(169.20)***
*LIST*lnAV*					−0.067	(−8.44)***
YR06	0.311	(15.55)***	0.295	(12.75)***	0.291	(12.58)***
YR07	0.350	(18.00)***	0.337	(14.16)***	0.333	(13.99)***
YR08	0.235	(11.83)***	0.200	(8.08)***	0.199	(8.05)***
YR09	−0.101	(−4.66)***	−0.156	(−5.83)***	−0.156	(−5.85)***
YR10	−0.089	(−3.93)***	−0.092	(−3.24)***	−0.094	(−3.31)***
*LIST*YR06*			−0.010	(−0.20)	−0.004	(−0.07)
*LIST*YR07*			0.024	(0.63)	0.032	(0.83)
*LIST*YR08*			0.094	(2.35)**	0.095	(2.39)**
*LIST*YR09*			0.158	(3.59)***	0.155	(3.52)***
*LIST*YR10*			0.004	(0.08)	0.006	(0.13)
NYC	0.101	(1.07)	0.097	(1.03)	0.090	(0.96)
LA	0.257	(1.92)*	0.252	(1.89)*	0.241	(1.81)*
CHI	0.964	(16.66)***	0.959	(16.57)***	0.951	(16.46)***
DC	0.326	(3.14)***	0.321	(3.09)***	0.314	(3.02)***
BOS	0.688	(3.95)***	0.687	(8.81)***	0.670	(8.61)***
IMR	0.615	(13.05)***	0.617	(13.04)***	0.638	(13.47)***
Coefficient estimates for 19 additional city-specific market dummies and 238 submarket dummies included in each model are not reported.						
$Adj\text{-}R^2$	0.782		0.783		0.784	
F	229		225		226	
N	15,884		15,884		15,884	

This table reports the Heckman selection-correction regression results to examine the correlation that providing seller list price information has with commercial real estate transaction prices. The dependent variable is logarithm of sale price. The selection-corrected model uses the probit specification from Model 4.2 to estimate the first stage (not reported) and construct the inverse Mill's ratio (IMR). The independent variables include the property assessed value, sale year, and market factors. The definitions of the independent variables are listed in Table 1. The t-values, based on hetroskedastic consistent errors, are reported in parentheses. The ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$ respectively.

Table 7. Regression estimates by price cohort.

(Selection-corrected stage 1 Dep. Var. = *LIST*, stage 2 Dep. Var. = *lnSP;* OLS Dep. Var = *lnSP*)

Independent variable	**(7.1) Stage 2 selection-corrected \$100,000 to \$10 M β (t-stat)**		**(7.2) Stage 2 selection-corrected \$100,000 to \$10 M β (t-stat)**		**(7.3) OLS \$10 M to \$500 M β (t-stat)**	
Intercept	6.100	(80.51)***	6.101	(78.62)***	6.573	(18.09)***
LIST	−0.056	(−4.98)***	−0.062	(−2.17)**	−0.147	(−2.93)***
lnAV	0.520	(111.22)***	0.520	(111.22)***	0.622	(47.33)***
YR06	0.303	(15.79)***	0.307	(13.71)***	−0.127	(−2.45)**
YR07	0.315	(17.09)***	0.312	(13.53)***	−0.011	(−0.20)
YR08	0.237	(12.67)***	0.227	(9.61)***	−0.075	(−1.32)
YR09	−0.078	(−3.86)***	−0.108	(−4.28)***	−0.453	(−6.21)***
YR10	−0.062	(−2.96)***	−0.043	(−1.58)	−0.319	(−4.67)***
*LIST*YR06*			−0.077	(−1.64)*		
*LIST*YR07*			0.003	(0.09)		
*LIST*YR08*			0.023	(0.63)		
*LIST*YR09*			0.086	(2.15)**		
*LIST*YR10*			−0.054	(−1.27)		
IMR	0.764	(18.57)***	0.769	(18.64)***		
Coefficient estimates for 24 city-specific market dummies and 238 submarket dummies included in each model are not reported.						
Adj-R²	0.611		0.612		0.703	
F	89		87		19	
N	14,050		14,050		1,834	

*This table reports the Heckman selection-correction and OLS regression results to examine the correlation that providing seller list price information has with commercial real estate transaction prices. The dependent variable is logarithm of sale price. The selection-corrected model uses the probit specification from Model 4.2 to estimate the first stage and construct the inverse Mill's ratio (IMR). The independent variables include the property assessed value, sale year, and market factors. The definitions of the independent variables are listed in Table 1. The t-values are reported in parentheses. The ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$ respectively.*

Table 8. Regression estimates for select locations.

(Selection-corrected stage 1 Dep. Var. = *LIST*, stage 2 Dep. Var. = *lnSP*)					
Independent variable	**(8.1) NYC β (t-stat)**	**(8.2) LA β (t-stat)**	**(8.3) CHI β (t-stat)**	**(8.4) BOS β (t-stat)**	**Benchmark All_Mkts β (t-stat)**
Panel A: city-specific estimates specified consistent with model 6.1 (select coefficient est. reported)					
LIST	−0.210 (−5.41)***	−0.069 (−1.83)*	−0.226 (−3.82)***	−0.193 (−2.88)***	−0.119 (−9.41)***
Adj-R2	0.763	0.722	0.749	0.815	0.782
F	209	191	217	147	229
Panel B: city-specific estimates specified consistent with model 6.2 (select coefficient est. reported)					
LIST	−0.263 (−2.62)***	0.009 (0.09)	−0.338 (−2.06)**	−0.273 (−1.75)*	−0.169 (−5.45)***
*LIST*YR06*	0.230 (1.39)	−0.176 (−1.10)	0.081 (0.31)	−0.024 (−0.68)	−0.010 (−0.20)
*LIST*YR07*	0.111 (0.87)	−0.201 (−1.72)*	0.232 (1.18)	−0.022 (−0.10)	−0.024 (0.63)
*LIST*YR08*	0.122 (0.94)	−0.120 (−0.97)	0.155 (0.27)	0.151 (0.76)	0.094 (2.35)**
*LIST*YR09*	0.186 (1.36)	0.221 (1.59)	0.369 (1.67)*	0.221 (1.02)	0.158 (3.59)***
*LIST*YR10*	−0.127 (−0.86)	−0.077 (−0.55)	0.046 (0.20)	0.143 (0.59)	0.004 (0.08)
Adj-R2	0.764	0.725	0.752	0.817	0.783
F	188	159	171	122	225
N	2,243	1,343	1,035	654	15,884

*This table reports the Heckman selection-correction regression results to examine the correlation that providing seller list price information has with commercial real estate transaction prices for select metropolitan areas. The dependent variable is logarithm of sale price. The selection-corrected model uses the probit specification from Model 4.2 to estimate the first stage (not reported) and construct the inverse Mill's ratio (IMR). The independent variables include the property assessed value, sale year, and market factors. The definitions of the independent variables are listed in Table 1. The t-values are reported in parentheses. The ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$ respectively.*

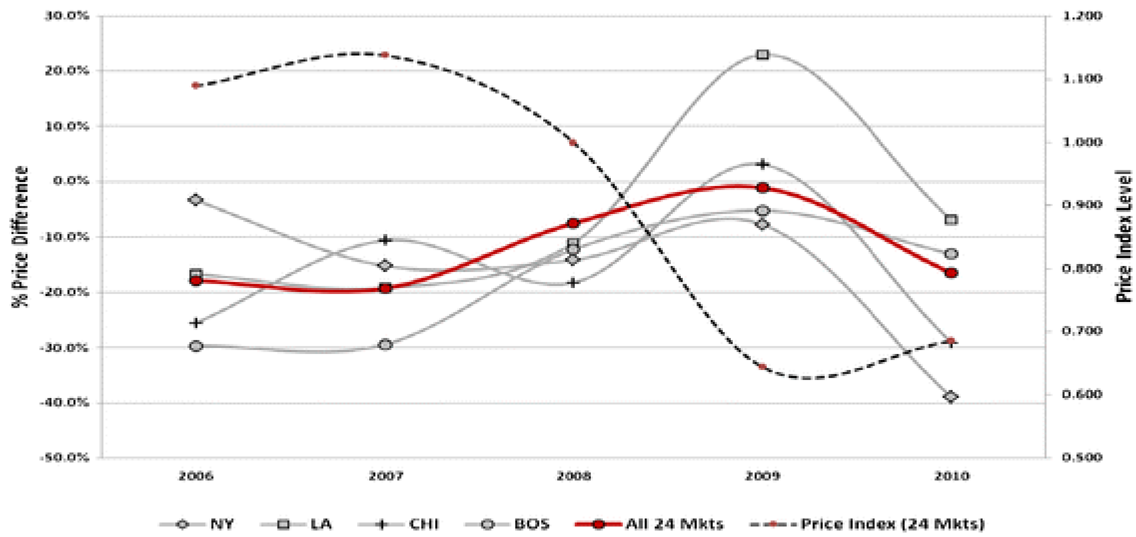

Figure 1. Sale price differences on properties marketed using list prices (graphed by location and time). This figure graphs the relative percentage sale price differences of properties marketed using list prices relative to those that did not. The figures, constructed from Table 7, Model 7.2 estimates for the U.S. (All 24 Mkts), as well as for New York (NY), Los Angeles (LA), Chicago (CHI) and Boston (BOS) are reported from 2006 to 2010. The price index (right axis) for all 24 markets is constructed from the estimated coefficients reported in Table 6, Model 6.2.

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