# Search Costs, Behavioral Biases, and Information Intermediary Effects

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## Abstract

Buyers in commercial real estate markets often pay different prices for comparable properties. We document that distant commercial real estate buyers pay, on average, a premium relative to local buyers, controlling for individual property characteristics as well as time fixed-effects. We test the extent to which the sources of these observed premiums are a product of higher search costs/information asymmetry problems associated with distance (search cost channel) or a result of reference-dependence preference/anchoring based on the price levels in the investors' home market (behavioral biases channel). Our results employing 114,588 industrial, multi-family and office sale transactions during 1997-2011 suggest the observed price premiums are explained by distant investors who face higher search costs and are at an information disadvantage compared to investors located in closer proximity to the property. In contrast, anchoring plays a more muted role in explaining the observed premiums. These results are robust to econometric techniques that control for potential unobserved property characteristics that are correlated with investor attributes. We also test the extent to which informational intermediaries affect the observed premiums and find that the use of a broker increases the acquisition prices of buyers and decreases the disposition prices of sellers. This result is consistent with the incentive real estate agents have to convince sellers to dispose of their properties too quickly and to convince buyers to search less and therefore pay higher prices.

*Key words:* Information Asymmetry, Anchoring, Search Costs, Agency Problems, Real Estate Pricing, Information Intermediaries, Brokers

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## Search Costs, Behavioral Biases, and Information Intermediary Effects

## 1. Introduction

Although markets have become increasingly integrated due to technological innovations and reductions in barriers across markets, several studies show that geographic distance still matters in behavioral, economic, and financial outcomes. These studies establish the relevance of geographic proximity to investor's costs of acquiring information, which in turn influences the behavior of both investors and firms as well as the pricing of assets. For example, John, Knyazeva, and Knyazeva (2011) show that investors in remotely located firms demand higher dividends due to increased information asymmetries about managerial decisions. Investor preferences toward local or domestic firms have also been widely documented (e.g., Coval and Moskowitz (1999), Ivkovic and Weisbenner (2005), Kedia, Panchapagesan and Uysal (2008)). In addition, Coval and Moskowitz (2001) show that mutual fund managers have better information about local firms and are able to earn higher returns on local investments. Using international data across 32 countries, Bae, Stulz, and Tan (2008) also document that local analysts make more precise earnings forecasts for firms in a given country than non-resident analysts, even after controlling for firm and analyst characteristics. Extending the effects of distance, Houston, Itzkowitz, and Naranjo (2011) examine the syndicated bank loan market and show that the geography and pricing of syndicated bank loans vary across countries conditional on information costs, cross-country differences in legal and regulatory costs, and cross-country competition in bank lending.

The effects of geographic distance manifest themselves through higher search costs related to information acquisition problems (e.g., degree of information asymmetry and uncertainty as well as other information and market impediments). In addition to distance effects, research has documented behavioral effects that are also related to information, but in this case investors use heuristics to process data and commit errors due to reliance on rules of thumb or past experience (e.g., Shefrin, 2002). For example, investors tend to invest in the best performing mutual funds in the past five years, using the rule of thumb that "past performance is the best predictor of future performance." Moreover, investors may suffer from behavioral biases where they are prone to "anchor" their perspectives and expectations on their local or personal circumstances. Although these heuristic-driven biases and anchoring effects should not affect fundamental values in efficient markets, they may drive transaction prices away from market values in inefficient markets.

Both distance effects and behavioral biases may lead to the payment of higher prices for a given investment at acquisition and to lower prices at disposition. These pricing outcomes may occur more frequently in segmented and informationally inefficient markets, such as commercial real estate (CRE) markets where the determinants of rental rates, and therefore current and future income streams and values, are determined in rental markets that are decidedly local in nature. Remote investors experiencing high search costs may search less and therefore pay higher prices compared to "local" buyers. In addition, investors may "anchor" their value estimates on prices observed in their home market. Thus, buyers coming from markets with higher average prices may pay premiums for properties in lower-cost areas. In this paper, we examine the magnitude and relative effects of geographical distance and behavioral biases on prices paid for CRE assets.

In analyzing potential distance and behavioral effects, it is inferentially critical to carefully control for attributes of the property and transaction. In fact, the Alchian-Allen theorem predicts that distant buyers will increase the quality of their consumption (investment) when faced with higher transactions costs. The estimated price differential associated with distant buyers could therefore be biased because of omitted quality characteristics correlated with distance. Unlike previous studies, we use a methodology developed by Harding, Rosenthal, and Sirmans (2003) that explicitly controls for the potential influence of unobserved property characteristics correlated with investor attributes. We also disentangle potential search cost effects from behavioral bias effects. Finally, we examine the extent to which information intermediaries, such as brokers, alleviate or exacerbate deviations from market values. Using an intermediary can potentially reduce search costs and attenuate behavioral biases. However, real estate agents have a self-serving incentive to convince owners (buyers) to sell (buy) their properties too quickly (Levitt and Syversun (2008)).

We find that distant buyers pay a price premium relative to local buyers in the fifteen largest US CRE markets. These price premiums exist across property types as well as over real estate cycles. In decomposing the source of these price premiums, we find that search costs associated with distance are both economically and statistically significant in explaining observed price premiums; in contrast, behavioral biases in the form of anchoring effects tend to play a less important role in the determination of negotiated transaction prices. These results are confirmed with the use of econometric procedures that more fully account for potential unobserved property characteristics correlated with investor attributes. Finally, we find that the use of a brokerage services increases the acquisition prices of buyers and decreases the disposition prices of sellers, consistent with the agency problems reported in Levitt and Syversun (2008).

The rest of the paper is organized as follows. Section 2 provides a brief review of the literature. Section 3 provides a pricing framework for estimating information asymmetry and anchoring effects while accounting for the influence of a property's unobserved characteristics that are potentially correlated with investor attributes. Section 4 describes our empirical model, while Section 5 contains a data description and summary statistics. Our regression results are presented and discussed in Section 6. Section 7 summarizes the analysis and offers some concluding comments.

## 2. Background Literature

The effect of distance on the investment decisions and returns has received considerable research attention, with a particular research focus on investors' preferences towards local or domestic firms (Foad (2012), Abreu, Mendes and Santos (2011), Ivkovic and Weisbenner (2005), Kedia, Panchapagesan and Uysal (2008), Strong and Xu (2003), and Coval and Moskowitz (1999)). Another stream of literature presents evidence that better informed investors are able to earn higher returns (Coval and Moskowitz (2001)). John, Knyazeva, and Knyazeva (2011) further show that investors in remotely located firms demand higher dividends due to increased information asymmetries about managerial decisions.

In real estate markets, the existing literature provides mixed evidence on the effects of distance on transactions prices, in part because of the varying property types examined, sample sizes used, and methodologies employed. Earlier studies using housing markets and small samples suggest that there are no price differences associated with distance. For example, Turnbull and Sirmans (1993) use a small sample of housing transactions from Baton Rouge, Louisiana and conclude that there are no price differentials across local (informed) and distant (uniformed) buyers. In contrast to this earlier literature, more recent work on housing prices suggests there are distance effects in housing prices. Ihlanfeldt and Mayock (2012), for example, use a large number of single-family home sales in Florida and present evidence supporting the hypothesis that buyers with higher search costs pay a premium to acquire their homes. They also provide evidence supporting an anchoring hypothesis whereby buyers coming from high price markets pay more for their homes.

There is little research on the impact of higher search costs and anchoring in CRE markets. Lambson, McQueen, and Slade (2004) examine CRE prices paid by out-of-state buyers of apartments in the Phoenix metropolitan area from 1990-2002. Their results provide weak evidence suggesting that out-of-state premiums can be partially explained by search cost disadvantages and by investor anchoring, primarily from a California effect (half of their out-of-state sample consists of California properties). A key limitation of the Lambson, McQueen and Slade (2004) study is that it is based on one market and one property type. In addition, the coefficient estimates on their out-of-state buyer variable captures information asymmetry and/or anchoring effects, as well as the unobserved characteristics of the types of properties in which these buyers tend to invest. Finally, out-of-state investors may not necessarily be distant investors. For example, many investors from the states of NJ and CT are located within 50 miles of New York City and may not necessarily be at an information disadvantage to investors coming from the state of New York.

The "anchoring" phenomenon is drawn from the behavioral literature. Slovic and Lichtenstein (1971) and Tversky and Kahneman (1974) were the first to discuss heuristics and biases. The behavioral finance literature has examined two main areas of research: (1) managerial financing and investment decisions as rational responses to securities mispricing, and (2) the direct effect of managers' biases and nonstandard preferences on their decisions (Baker and Wurgler, 2011). These studies have been summarized by Shefrin (2002), Barberis and Thaler (2003), and Baker and Wurgler (2011). In the real estate literature, Northcraft and Neale (1987) present evidence of anchoring in property pricing that is similar for both amateurs and real estate professionals. Black and Diaz (1996), Diaz and Hansz (1997), Diaz and Wolverton (1998), and Diaz, Zhao and Black (1999) also find evidence of an anchoring effect in real estate prices.[1]

Bokhari and Geltner (2011) provide evidence that loss aversion plays a role in CRE pricing that varies across market participants and real estate cycles. They also provide some evidence of a possible anchoring effect. However, extending the implications of their findings to hedonic price indices, Bokhari and Geltner (2011) find that the impact of loss aversion is attenuated at the market level and conclude that pricing and transaction volumes were little affected by investor loss aversion during 2001-2009.

The role of intermediaries in mitigating information asymmetries and eliminating behavioral biases has been examined by Campbell and Kracaw (1980), Chan (1983), Lizzeri (1999), Allen and Santomero (2001), Anand and Subrahmanyam (2008), and Levitt and Syverson (2008), among others. Campbell and Kracaw (1980) point out that the role of intermediaries' can be economically significant in imperfect markets. Chan (1983) posits that when information asymmetry with positive search costs exists, a "lemons" market will prevail without intermediaries. In such a market, financial intermediaries can serve as informed agents that induce a Pareto-preferred allocation, leading investors to a higher welfare state. The role of expertise in reducing behavioral biases has been examined by Kaustia, Alho and Puttonen (2008).

Our research contributes to the literature by examining the influence of search costs (i.e., information asymmetry and uncertainty) and behavioral factors (i.e., anchoring) on prices paid by

[1] Additional evidence of anchoring in real estate is seen in appraisal smoothing. A large body of literature discusses smoothing in appraisal based indexes due to appraisal values lagging true prices and being too reliant on historical prices (Geltner (1989).

local versus distant buyers, controlling for unobserved property and investors characteristics. In addition, we establish to what extent these effects vary across markets, by property types, and over time. We also test the extent to which using local intermediaries (i.e., brokers) attenuates or magnifies price premiums or discounts.

## 3. Pricing Framework

To identify empirically potential price differential effects due to differential search costs, behavioral biases, and the use of information intermediaries, we adapt the hedonic valuation methodology developed by Harding, Rosenthal, and Sirmans (2003). Let a commercial property be defined by a bundle of characteristics, $C_i$. The vector of shadow prices corresponding to $C_i$ is defined as $s_i$.

In a perfectly competitive market, buyer and seller characteristics, including their relative bargaining position and ability, would not affect transaction prices as all market participants would be price takers. However, in relatively illiquid, segmented, and informationally inefficient CRE markets, negotiated transaction prices may vary from the "true" (but unobservable) market value of the property. The transaction price of property, $P_{it}$, can therefore be presented as:

$$P_{it} = s_{it}C_{it} + B_{it} , \tag{1}$$

where $B_{it}$ is an additive term that captures the net effect of the buyer's and seller's characteristics, including search costs and behavior biases, on the observed transaction price. A positive (negative) $B_{it}$ indicates the seller (buyer) has, on net, the bargaining/information advantage. After dropping subscripts to simplify notation, $B$ can be represented as:

$$B = \alpha^B D^B + \alpha^S D^S + e_B, \tag{2}$$

where $D^B$ is a vector of buyer characteristics and $\alpha^B$ is a vector of shadow prices that measures the transaction price impact of these buyer characteristics. $D^S$ and $\alpha^S$ are similarly defined for sellers.

For ease of exposition, assume initially that buyers and seller differ only with respect to their search costs, as proxied for by the distance between their home address and the location of the transacted property. More specifically, assume the vector $D^B$ contains a dummy variable set equal to one if the buyer resides in a distant market; zero if the buyer resides in the local market. Similarly, $D^S$ indicates whether the seller resides in a distant market. The coefficients $\alpha^B$ and $\alpha^S$ reflect the effects of geographical distance on search costs and bargaining power. Substituting equation (2) into (1) yields:

$$P = sC + \alpha^B D^B + \alpha^S D^S + e_b \, . \tag{3}$$

Although search costs (and other buyer and seller characteristics) may affect negotiated prices, the HRS identification strategy recognizes that search costs (distance) may also affect the demand for unobserved (quality) attributes of the property. Thus, buyer and seller search costs may be correlated with unobserved attributes of the property, resulting in biased estimates of the distance coefficients $\alpha^B$ and $\alpha^S$.

To demonstrate this bias, suppose most of the property characteristics that comprise $C$ are observable in the dataset and denoted as $C^O$. However, assume some property characteristics, $C^U$, are known by the buyer and seller, but unobservable in the dataset. Then, $sC$ can be decomposed as:

$$sC = s^O C^O + s^U C^U + e_h. \tag{4}$$

That is, there is a vector of shadow prices associated with unobservable, as well as observable, property characteristics. Because both buyers and sellers value these unobservable property characteristics, $C^U$ may be correlated with $D^B$ and $D^S$. The relation between the value of the unobserved characteristics and the distance of the buyer and seller from the transacted property can be written as:

$$s^U C^U = \beta^B D^B + \beta^S D^S + e_i \, . \tag{5}$$

Substituting (5) into (4) we obtain:

$$sC = s^O C^O + \beta^B D^B + \beta^S D^S + e_j \, , \tag{6}$$

which can be substituted into (3) to yield:

$$P = s^O C^O + \beta^B D^B + \beta^S D^S + \alpha^B D^B + \alpha^S D^S + e_j + e_b \, . \tag{7}$$

Rearranging, equation (7) can be presented as:

$$P = s^O C^O + (\alpha^B + \beta^B) D^B + (\alpha^S + \beta^S) D^S + e_{.} \tag{8}$$

Equation (8) can be estimated by regressing the sale price of a sample of properties on the observable characteristics of the properties and dummy variables indicating whether the buyers and sellers are distant (i.e., non-local). To provide a benchmark, we first estimate this traditional hedonic specification. However, it is clear from equation (8) that estimates of the coefficients on $D^B$ and $D^S$ will be biased because they are a composite of distance (search costs) effects ($\alpha^B$ and

$\alpha^S$) and demand effects ($\beta^B$ and $\beta^S$); more specifically, buyer and seller demand for unobserved property characteristics correlated, in this application, with distance from the property.

Moreover, it is likely the confounding of distance effects and demand effects will bias upward the estimated coefficients on $D^B$ and $D^S$. The Alchian-Allen theorem predicts distant buyers will increase the quality of their consumption (investment) when faced with higher transactions costs. In CRE markets, distant owners have higher costs than local owners both in their initial searches and their subsequent management of the property. As a result, distant owners are more likely to purchase, for example, properties with relatively low vacancy rates that are subject to longer-term, triple-net leases to national credit tenants. In contrast, local investors are better able to manage the risks of more management-intensive properties with deferred maintenance, high tenant turnover, and little economies of scale.

Information on occupancy and lease details are not available in the CoStar data.[2] However, properties subject to triple-net leases with national credits are more likely to be owned by passive and possibly distant investors and to sell at higher per square foot prices than the more management-intensive properties purchased by small, local investors. As a result, the buyer's and seller's characteristics are correlated with the buildings' unobservable characteristics. Previous CRE studies, however, have not corrected for the significant bias these correlated omitted variables may produce (e.g., Turbull and Sirmans (1993) and Ihlanfeldt and Mayock (2012) for housing markets and Lambson, McQueen, and Slade (2004) for the commercial real estate markets). Moreover, these studies focus on the impact of search costs and anchoring biases faced by buyers, ignoring the potential information advantages and disadvantage of sellers.

Following Harding, Rosenthal, and Sirmans (2003), we control for these potential omitted variables biases by imposing two conditions on buyer and seller characteristics:

1. Symmetric bargaining power among buyers and sellers: $\alpha^B = -\alpha^S$
2. Symmetric demand for unobserved property characteristics: $\beta^B = \beta^S$

In the context of search costs due to distance, the first condition holds that distant buyers and sellers are equally disadvantaged relative to local sellers and buyers. More specifically, the price discount distant sellers are willing to accept due to their higher search costs is, on average, equal to the average premium distant buyers are willing to pay. The second symmetry condition holds that if distant (relative to local) buyers value an unobserved property characteristic, this same characteristic is equally valued by distant (relative to local) sellers.

[2] CoStar does provide information on the occupancy, gross and net operating income of some of the buildings in our sample. However, these fields are sparsely populated.

Imposing these conditions, we can re-write equation (8) as:

$$P = s^O C^O + (D^B - D^S)\alpha + (D^B + D^S)\beta + \varepsilon \,. \quad (9)$$

Equation (9) can be estimated by regressing sale prices on observable property characteristics ($C^O$), as well as and the difference ($D^B - D^S$) and sum ($D^B + D^S$) of the dummy variables indicating whether the buyer and seller are distant.[3] For example, in our empirical analysis we calculate the distance between the transacted property and the buyer's and seller's locations. If that distance is less than 50 miles, we classify the buyer (seller) as being located in close proximity to the property; otherwise, we identify the buyer (seller) as distant.[4]

In equation (9), $\alpha$ captures the impact of buyer and seller distance on $P$, whereas $\beta$ captures the impact of unobserved property characteristics that are correlated with distance on transaction prices. If the estimated coefficient on $\alpha$ is positive and significant, this suggests that distant buyers pay more (and distant sellers accept less), all else equal. If the estimated coefficient on $\beta$ is positive and significant, this result suggests that there are statistically important unobservable property characteristics, correlated with the location of buyers and sellers. Thus, equation (9) can be used to test for the impact of geographical distance on transaction prices, while controlling for the impact of unobserved property characteristics correlated with investors characteristics.[5] It is important to note that if the symmetry conditions do not hold precisely, our empirical estimations will understate the true effects of distance on prices. The upper bound of the effect will be given by the baseline dummies estimates.

In our empirical analysis, we expand the buyer and seller characteristics in vectors $D^B$ and $D^S$ to include proxies for the existence of both anchoring and information intermediary effects, in addition to distance proxies. With respect to anchoring, condition 1 above holds that the price premium paid by buyers coming from more expensive markets is equal to the price discount sellers from (proportionately) cheaper markets are willing to accept. Condition 2 holds that buyers coming from more expensive markets value unobserved property characteristics similarly to sellers from a more expensive market. With respect to the use of intermediaries, condition 1 holds that, on average, the use of a buyer's broker results in a price premium (discount) equal in magnitude to the discount (premium) associated with the use of sellers' brokers. Finally, condition 2 holds that

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[3] If both the buyer and seller are distant, $D^B - D^S = 0$ and $D^B + D^S = 2$. If both the buyer and seller are local, $D^B - D^S = 0$ and $D^B + D^S = 0$. If the buyer is distant and the seller local, $D^B - D^S = 1$ and $D^B + D^S = 1$. Finally, if the buyer is local and the seller is distant, $D^B - D^S = -1$ and $D^B + D^S = 1$.

[4] We employ different mileage breakpoints to test the robustness of our results.

[5] Note that, with respect to distance, there is no omitted intermediate group. Thus, a second set of differences is redundant in the specification since they are perfectly collinear with the first set (e.g., buyers that are not classified as distant buyers ($BF$) are classified as local buyers, so these two groups sum to 1).

the demand for unobserved property characteristics does not vary among buyers and sellers involved in a transaction without a broker.

## 4. Empirical Methodology

Following our pricing model framework presented in equation (9), we employ a semi-log hedonic regression model. Our preferred regression model for our office and industrial samples has the following form:

$$\begin{aligned} LNPRICE_i = {} & \phi + \alpha_1(BF - SF) + \beta_1(BF + SF) + \alpha_2(BE - SC) + \beta_2(BE + SC) + \alpha_3(BB - SB) + \beta_3(BB + SB) \\ & + \lambda_1 SAMEB + \lambda_2 NOB + \lambda_3 PRICEVOL + \lambda_4 LIQUIDITY + \lambda_5 AGE + \lambda_6 AGE2 + \lambda_7 SFQ + \lambda_8 SFQ2 \\ & + \lambda_9 LANDSF + \lambda_{10} LANDSF2 + \lambda_{11} FLOORS + \sum_{c=1}^{2} \delta_c CLASS_c + \sum_{i=1}^{5} \beta_i COND_i + \sum_{j=1}^{5} \lambda_j MATERIAL_j \\ & + \sum_{n=1998}^{2011} \chi_n YR_n + \sum_{p=2}^{P} \sigma_p SPTDUM_p + \sum_{m=2}^{m} \delta_m SMDUM_m + \lambda_{12} LONG + \lambda_{13} LAT + \lambda_{14} AVALUE + \varepsilon_m \end{aligned} \quad (10)$$

where:

| | |
|---|---|
| *LNPRICE* | The natural logarithm of the sale price; |
| *Φ* | A constant term; |
| *BF* | A category variable indicating a distant buyer ($D^{BF}$); set equal to one if the buyer's address is 50 miles or more from the property's address; |
| *SF* | A category variable indicating a distant seller ($D^{SF}$); set equal to one if the seller's address is 50 miles or more from the property's address; |
| *BE* | A category variable indicating the buyer is from an expensive market ($D^{BE}$); set equal to one if the difference between the median price/sf in the buyer's home market and the median price/sf observed in the market in which the transacted property is located greater than the average of differences for all buyers in the market. |
| *SC* | A category variable indicating the seller is from a cheaper market ($D^{SC}$); set equal to one if difference between the median price/sf in the seller's home market and the median price/sf observed in the transacted property's market is less than the average of differences for all sellers in the market. |
| *BB* | A category variable ($D^{BB}$) set equal to one if the buyer is represented by a broker; |
| *SB* | A category variable ($D^{SB}$) set equal to one if the seller is represented by a broker; |
| *SAMEB* | A category variable set equal to one if the seller and buyer are both represented by the same brokerage firm; |
| *NOB* | A category variable set equal to one if neither the seller nor buyer were represented by a broker or if such information is missing; |
| *PRICEVOL* | The square of the residual from a hedonic regression used to predict the selling price of the property; estimated by property type, year and zip code, using the standard structural characteristics, and controlling for location; |
| *LIQUIDITY* | The number of transactions by year, property type and zip code; |

| | |
|---|---|
| *AGE* | Age of the structure(s) in years; |
| *AGE2* | The square of *AGE*; |
| *SQFT* | Total square footage of structure(s) in thousands; |
| *SQFT2* | The square of *SQFT*; |
| *LANDSF* | Land square footage in thousands; |
| *LANDSF2* | The square of *LANDSF*; |
| *FLOORS* | Number of floors in property; |
| $CLASS_c$ | An indicator variable describing the overall quality of the property: *CLASSA* and *CLASSB* denote Class A and Class B properties, respectively. The omitted (lower) class is *OTHER*; |
| $COND_i$ | An indicator variable denoting property condition: *CONDNA, EXCL*, *GOOD*, *NEEDSIMPR*, *POOR* denote missing, excellent, good, needs improvements, and poor condition, respectively. The omitted condition is adequate, *ADEQ*; |
| $MATERIAL_j$ | An indicator variable denoting construction material; *MATERIALNA*, *METAL*, *CONCR*, *STEEL*, and *WOOD* denote missing, metal, reinforced concrete, steel and wood construction, respectively. The omitted material is masonry, *MASONRY*; |
| $YR_n$ | A binary variable indicating the year of the sale transaction: 1998-2011; 1997 is the omitted year; |
| $SPTDUM_p$ | A category variable indicating the subproperty type of the building; |
| $SMDUM_s$ | a category variable indicating in which CoStar defined submarket the transacted property is located; |
| *LONG* | Longitude coordinate of the property; |
| *LAT* | Latitude coordinate of the property; |
| *AVALUE* | Assessed value of the asset for property tax purposes; |
| $\varepsilon_m$ | An error term. |

According to Clapp and Giacotto (1992, pg. 301), "assessed value summarizes into a single number the locational and structural characteristics of a real property." Thus, to better control for omitted locational and structural characteristics that are correlated with buyer and seller distance, anchoring, and the use of brokerage services, we include assessed value (in $millions) as an additional explanatory variable. To further control for any bias that may result from omitted locational and structural characteristics that are correlated with our main variables of interest, we include fixed effects for the subproperty type of the structure and the CoStar defined submarket in which the property is located. In effect, equation (9) compares properties purchased by buyers and sellers that are distant, that come from more expensive markets, and that use brokerage services within the same geographic submarket and subproperty type. In our multifamily regression models, we also include the number of units in the property and the number of one and two bedroom apartments.

## 5. Data and Summary Statistics

We obtain commercial property transaction data from CoStar for the period of January 1997 through June 2011. We focus on the fifteen largest U.S. metropolitan areas by total number of CoStar recorded transactions: Atlanta, Boston, Chicago, Dallas/ Ft Worth, Denver, East Bay /Oakland, Los Angeles, New York City, Phoenix, San Diego, San Francisco, Seattle, South Florida, Tampa/St. Petersburg, and Washington DC. In addition, we restrict our analysis to industrial, apartment, and office properties with a recorded sale price of at least $500,000. Retail properties, hotels, manufactured housing, and other special-use properties are excluded from the analysis.

The original dataset contains 177,705 CoStar verified transactions across the three property types and fifteen metropolitan markets. We eliminate transaction records missing one or more of the variables defined above required for our hedonic regressions. This reduces our usable sample by 18,372 observations. We also exclude sale transactions associated with a "special condition," including sales that are part of an auction, sales of apartments to be converted to condominiums, sales that involve the use of Section 1031 tax-deferred exchanges, sale-leaseback transactions, as well as sales that involved damage from natural disasters, building contamination, or the threat of contamination. The elimination of these non-arms-length and other "atypical" transactions further reduces our sample by 41,402 observations. Finally, we eliminate 3,321 observations for which we are not able to calculate the median price per square foot in both the buyer's and seller's home market (by year and by property type). Our final regression sample consists of 114,588 observations, of which 34,733 are industrial properties, 48,318 are apartments, and 31,537 are office property transactions.

Summary statistics for our final sample are presented by property type in Table 1. Panel A contains the mean values of site and structural characteristics. Industrial properties in our sample have a mean transaction price of $2.1 million, are 27 years old, contain an average of 38,230 square feet large of constructed space, and are built on land parcels that average 137,160 square feet. On average, apartment properties in our sample sold for $3.9 million, are 48 years old, contain 39,500 square feet of space, and are built on parcels that average 107,380 square feet. Office properties in the sample sold for an average price of $7.2 million, are 33 years old, 38,260 square feet large, with a lot size of 85,840 square feet.

Only 2 percent and 8 percent, respectively, of the industrial and office transactions involved "Class A" properties. Clearly, our CoStar database is more representative of the universe of CRE properties than a sample based exclusively on "institutional quality" properties. The dominant property condition for all three property types is adequate; the most frequent construction type is masonry. The exception is multifamily properties, 23 percent of which are wood construction. Note, for example, that property condition is missing in 35 percent of the industrial sale observations; the primary construction material is missing in 23 percent of the industrial sample. Rather than dropping these observations we create two category variables that are set equal to one, if property condition or construction material is missing.

Panel B of Table 1 presents the distribution of sale transactions by property type and year. Transaction volumes increased steadily from 1997 until 2006 among all property types. For example, 45 percent of our industrial sales occurred in 2004-2007. This concentration reflects the CRE boom that occurred during this period. However, a portion of the growth in transaction volume also reflects CoStar's expanding and improving coverage over the sample period. The year 2007 marks the beginning of a market downturn and a substantial decrease in CRE sale transactions. Note that the 2011 sample contains transactions from January through June.

Panel C of Table 1 provides mean values for our main variables of interest. As discussed above, these variables are constructed to proxy for the degree of asymmetric information due to distance effects, potential price/value anchoring biases, and the impact of information intermediaries. Panel C also contains mean values for our measures of market liquidity and price uncertainty, as well as the percentage of transactions in which both the buyer and seller were represented by the same broker (*SAMEB*) and the percentage of transactions that did not involve a broker (*NOB*).

For each sale record we first measure the distance in miles between the buyer's home address and the transacted property (*BDIST*), as well as the seller's home address and the property (*SDIST*). Distance is calculated based on the longitude and latitude coordinates of the transacted property and the buyer's and seller's listed address. Longitude and latitude coordinates for the transacted property are provided by Costar; the buyer's and seller's coordinates are estimated based on the buyer's and seller's street addresses.[6]

On average, buyers are located 88 (industrial) to 100 (multifamily) miles from the transacted property; sellers are located 101-110 miles from the sold property. However, there is a

[6] Buyer distance is calculated based on the following equation: DISTANCE_PROP_BUYER= (7921.6623*arsin(sqrt((sin((0.0174532925199433*latitude_property-0.0174532925199433 *latitude_buyer)/2))**2 +cos(0.0174532925199433*latitude_buyer)*cos(0.0174532925199433 *latitude_property)*(sin((0.0174532925199433*longitude_property-0.0174532925199433* longitude_buyer)/2))**2))). The distance between the seller's home market and the transacted property is similarly calculated.

great deal of variation in distance from the transacted property. For example, although the average multifamily buyer is located 100 miles from the property, *BDIST* and *SDIST* range from approximately 1 to 2,700 miles. We define a "distant" buyer, *BF*, as one whose listed address is more than 50 miles from the transacted property. Similarly, a distant seller, *SF*, is defined as one whose listed address is more than 50 miles from the transacted property. In our sample of largely non-institutional quality properties, it is interesting to note that only 10 to 12 percent of buyers and 13 to 14 percent of sellers reside more than 50 miles from the transacted property.

We next measure the difference in median per square foot transaction prices between the buyer's home market and the market that contains the transacted property.[7] We calculate median prices for each market by year, by property type, and by zip code. If a median price for a property type cannot be calculated by zip code because of a lack of sale transactions in that year, we use transaction sales data aggregated at the town level. If there are insufficient transactions at the town level, we use transactions aggregated across the entire metropolitan area to calculate median transaction prices.

The largest average difference in median prices between the buyer's home market and the market that contains the transacted property (*BPRICEDIFF*) is observed among multifamily properties. On average, the median price in the apartment buyer's home market is $22 per square foot higher than the corresponding median price per square foot in the market in which the transacted property is located. The corresponding average apartment price differential between the seller's home market and the property (*SPRICEDIFF*) is $17 per square foot. The observed price differentials are substantially smaller in the office and industrial samples.

We classify the buyer in a transaction as coming from a more expensive market (*BE*) if the average per square foot price difference in a given year (based on differences in median prices) between the buyer's home market and the transacted property's market is greater than the median price difference for each property type in that year. Similarly, a seller is classified as coming from a less expensive market (*SC*) if the difference between the median per square foot price in seller's market and the transacted property's market is less than the average for that property type in that year. Using these definitions, 31 percent of buyers in the multifamily sample are classified as coming from a relatively more expensive market; 71 percent of apartment sellers reside in less expensive home markets. These percentages are strikingly similar in magnitude in the office and industrial samples.

[7] We only report statistics based on median price differences given the right skewness of the data, which results in biased averages even after winsorizing at the 0.01% level.

According to CoStar, 45 percent of multifamily sellers and 47 percent of industrial and office property sellers were represented by a broker. Interestingly, CoStar reports that 30 to 36 percent of the buyers in our sample were represented by a "buyers" broker. As previously discussed, both buyers and sellers may be ill-served by brokers who are better informed (Levitt and Syverson, 2008), despite the degree to which many buyers and sellers rely on brokers to reduce their search costs and improve pricing outcomes. In 13 percent (office) to 21 percent (multifamily) of transactions, the same brokerage firm represented both the buyer and seller. However, in 49 to 50 percent of transactions, neither party employed a broker.

We also measure the volume of sale transactions by property type, year and zip code. The multifamily market has experienced, on average, the highest number of transactions (654), while the office market has the lowest average number of sales (251) per year and zip code. These three time-series of transaction volumes, defined as *LIQUIDITY*, proxy for the aggregate market liquidity (turnover) of each property type. Our proxy for price uncertainty, *PRICEVOL*, is calculated as the square of the residual from a hedonic regression by property type, year, and zip code, using standard site and structural characteristics, as well as controls for submarket location. Higher values of *PRICEVOL* are observed when observed transaction prices are more difficult to predict with our hedonic regression model.

Table 2 presents the pairwise correlations for our main regression variables. The observed correlations between the natural log of price and the main property structural characteristics are as expected. In addition, we note that *SAMEB* and *PRICEVOL* are positively correlated with price, while *NOB* and *LIQUIDITY* are negatively correlated with price. Furthermore, we observe that sale prices are positively correlated with *BF* (distant buyer) and *BE* (buyer from expensive market). Although *SF* (distant seller) is also positively correlated with price, this correlation is not as large as the correlation of *BF* and *LNPRICE*; furthermore *SC* (seller from a cheap market) is negatively correlated with price. These correlations are also largely consistent with our predictions.

The positive correlations of both *BF_SF_DIF* and *BF_SF_SUM* with *LNPRICE* suggest that the large positive correlation coefficients observed for *BF* and *SF* with price may be due to unobserved characteristics of properties transacted by these types of investors, rather than a pure distance effect. Indeed, it is apparent that both distant buyers and sellers (*BF* and *SF*) tend to acquire newer and larger properties, as the correlations between *BF* (*SF*) and *AGE*, *SF* and *LANDSF* are all statistically significant and equal to -0.1316, 0.2976 and 0.0213 (-0.1008, 0.2131, 0.0157), respectively. However, the observed correlations of property characteristics with *SF* are lower than with *BF*. This is intuitive because distant sellers are distant buyers at acquisition of the property and naturally over time, during their investment period, properties age and become relatively smaller compared to newer properties, due to changing development standards. In addition, we observe that buyers from more expensive markets (*BE*) buy newer and larger properties, while sellers from less expensive markets sell older and smaller properties.

We also note that *BF* (*BE*) and *SF* are significantly positively correlated, while *BE* is significantly negatively correlated with *SC*, suggesting that distant buyers from expensive markets are matched with distant sellers from expensive markets.

## 6. Regression Results

Table 3 contains the results from separately estimating equation (10) for our industrial, multifamily, and office property samples. The observations from the 15 metropolitan areas are pooled to construct the regression sample for each property type. The dependent variable is the natural log of the sale price. An advantage of using the log of sale price as the dependent variable is that less weight is given to extreme values than when using untransformed prices.[8] T-statistics are reported in parentheses; *, **, and *** denote statistical significance at the 10, 5, and 1 percent level, respectively.

In the industrial and office samples, we include sub-property type fixed effects. We control for the effects of location by including submarket fixed effects and geographic coordinates. The submarkets are defined by CoStar based on discussions with local brokers. These submarket delineations are preferable to the use of zip codes and census-tract groups, neither of which are constructed specifically to capture true commercial property submarkets. In our final sample, we identify 595 distinct CoStar delineated submarkets across our 15 industrial property markets; 553 distinct submarkets in our multifamily sample, and 629 submarkets in our office property sample.

Our baseline model explains 60.0 percent of the variation in logged sale prices in the industrial sample. The adjusted R-squared for the multifamily and office baseline regressions are 75.5 and 75.1 percent, respectively. It is important to note that this baseline specification does not use the model developed by Harding, Rosenthal, and Sirmans (2003) to control for unobserved characteristics correlated with the characteristics of the buyer and seller. Therefore, the estimated coefficients on our key variables of interest, *BF*, *SF*, *BE*, *SC*, *BB*, and *SB* represent the upper bounds of the pricing effects associated with distance, anchoring, and the use of brokers. These coefficient estimates are reported at the top of Table 3, along with the estimated coefficients for

[8] With this semi-log functional form, the percentage price effect with a unit change in a property characteristic is obtained by (exp(coefficient)-1)*100.

our "same broker" and "no broker" variables and our price uncertainty and market liquidity proxies.

Table 3 also contains coefficient estimates and t-statistics for our site and structural characteristics, including assessed value, as well as our transaction year fixed effects. We first discuss the coefficient estimates for these hedonic control variables. As expected, the estimated coefficient on property *AGE* is negative and highly significant in the industrial, multifamily, and office property samples. However, the estimated coefficient on *AGE2* is positive and significant in all three property type samples. This quadratic relation between price and age suggests a positive "vintage" effect for older properties. The estimated coefficients on *SQFT* and *LANDSF* are positive and highly significant, as expected. However, the estimated coefficients on *SQFT2* and *LANDSF2* are, with one exception, negative and significant. These results strongly suggest the relation between sale price and both building size and lot size is nonlinear. In our apartment sample, sale prices are positively associated with the number of units in the property, the number of the units that contain two bedrooms, and the number of floors in the property.

The variable $CLASS_c$ is included to control for variation in the overall quality of the property. Class B office properties sell at higher prices, on average, than properties rated Class C or lower. Moreover, the price premium associated with Class A properties is even larger that the premium associated with Class B properties. Class B industrial properties also sell at higher prices than properties rated Class C or lower. However, no significant price premium for Class A properties is detected in the industrial sample.

The variable type $COND_i$ is included in the estimation of equation (10) to control for cross-sectional variation in CoStar's qualitative assessment of building condition. Buildings in "adequate" condition are used as the control group. Thus, we expect a positive relation between selling price and buildings deemed to be in excellent (*EXCEL*) or good (*GOOD*) condition. We expect a negative relation between selling price and buildings categorized by CoStar as in need of improvement (*NEEDSIMP*) and those classified as being in poor condition (*POOR*). To control for missing building condition data, we also create an indicator variable (*CONDNA*) that is set equal to one if building condition is missing in the sale record. As expected, the estimated coefficients on *EXCEL* and *GOOD* are positive and significant with the exception of the industrial sample in which the estimated coefficient on *GOOD* cannot be distinguished from zero. The estimated coefficients on *NEEDSIMP* and *POOR* are negative and statistically significant, with one exception.

The inclusion of *$MATERIAL_i$* is intended to control for cross-sectional variation in construction materials. Masonry construction is the most common and is therefore used as the control type. We also create a dummy variable (*MATERIALNA*) that is set equal to one if the primary type of construction material is missing in the sale record. The estimated coefficient on *WOOD* is consistently negative and significant across the three property types, indicating this construction material is associated with lower transaction prices relative to masonry construction. In contrast, the estimated coefficient on reinforced concrete (*CONCR*) and *STEEL* are largely positive and statistically significant. A strength of our class, building condition, and building material variables is that they are likely to be correlated with other unobserved indicators of the property's quality. The estimated coefficient on *AVALUE* is negative and significant in the multifamily sample. This result reflects the margial contribution of *AVALUE*, after including a broad range of common locational and physical characteristics.

Indicator variables for each year (*$YR_i$*) are included to control for the effects of time on sale prices; 1997 is used as the base year. The increasing magnitude of the estimated year fixed effects indicates significant price appreciation from 1998 until 2007, followed by statistically significant price decreases from 2008 to 2011. The largest price appreciation during the boom period is observed in the multifamily market; the largest drop in prices post 2007 is observed in the office sample.

We next examine the coefficient estimates on our proxies for asymmetric information/search costs, reported in the first two rows of Table 3. If physical distance from the transacted property increases asymmetric information and search costs, the estimated coefficient on *BF* should be positive and significant; the coefficient on *SF* should be negative and significant. However, it is important to emphasize that if, on average, both distant buyers and distant sellers tend to buy larger and higher quality properties, the estimated coefficients on *BF* and *SF* will be positive and significant in the absence of perfect controls for property quality. Nevertheless, the estimated coefficient on *BF* should be larger in magnitude than the coefficient on *SF*.

The estimated coefficient on *BF* is positive and highly significant for all three property types. For example, the estimated coefficient on *BF* in the industrial property regression is 0.2356. This translates into a 26.6 percentage point price effect, all else equal. The corresponding percentage price effect for *BF* in the multifamily and office regressions is 13 percent and 49.5 percent, respectively. These baseline results suggest that distant buyers, with higher acquisition costs of information, pay significant price premiums. Although positive and statistically significant in all three property type regressions, the estimated coefficient on *SF* is much smaller in magnitude. Overall, these results strongly support the hypothesis that distant buyers pay price premiums, all else equal. That is, asymmetric information and search costs appear to reduce the bargaining power of distant buyers.

We next report our tests for the existence of an anchoring bias. The estimated coefficient on *BE* captures the extent to which buyers coming from more expensive markets "anchor" their "bid" prices to the higher prices in their home markets. Similarly, the estimated coefficient on *SE* captures the extent to which sellers who reside in less expensive markets anchor their "ask" prices to the lower prices in their home markets. If anchoring effects exist, the estimated coefficient on *BE* will be positive and significant; the estimated coefficient on *SC* will be negative and significant. In addition, in the presence of unobserved quality characteristics that are positively correlated with *BE* and *SC*, the estimated coefficients on both variables will be positive but the coefficient on *BE* will be larger in magnitude than the coefficient on *SC*.

The results presented in Table 3 support a significant anchoring effect for the office sample only. In the industrial and multifamily samples, the estimated coefficient on *BE* cannot be distinguished from zero; moreover, the estimated coefficient on *BE* of 0.0675 in the office sample is significantly smaller than the estimated coefficient on *SF*. In short, the results reported in Table 3 provide little support for the existence of an anchoring bias in CRE markets.

We now turn our attention to the coefficient estimates on our "broker" variables. The estimated coefficient on buyer broker (*BB*) is positive and highly significant across the three property types. That is, on average buyers who pay for brokerage representation pay significantly higher prices. This result is surely inconsistent with the expectations of buyer's who pay for brokerage services; however, it is consistent with the contention of Levitt and Syversun (2008) that brokers have an incentive to convince buyers to shut down their search too quickly and, as a result, pay higher prices. With the exception of the industrial sample, the estimated coefficient on seller broker (*SB*) is negative and highly significant. This result is again consistent with the hypothesis that brokers have a strong incentive to convince sellers to conclude their search for a buyer too quickly and, as a result, receive lower prices.

The estimated coefficient on *SAMEB* is positive and highly significant in the multifamily and office samples. At 0.1051, the coefficient is the largest in magnitude in the multifamily regression. This coefficient estimate translates to a 11.1 percent increase in the sale price, all else equal, when both buyer and seller employ the same brokerage firm. Again, buyers appear to be ill-served by brokers. In contrast, multifamily and office properties sales that do not involve a broker (*NOB*) transact at significantly lower prices, with discounts varying from 6.2 percent (for multifamily) to 13.5 percent (for office). This is consistent with our hypothesis that non-broker transaction prices may be lower due to investors sharing the cost reduction associated with not paying brokerage fees.

The estimated coefficient on *PRICEVOL*, which is equal to the actual transaction price minus the predicted (model) price, is negative and highly significant in all three specifications. This suggests that price/valuation uncertainty increases required returns and therefore depresses transaction prices. Increased liquidity (proxied for by transaction volume) is also associated with lower prices in industrial and office markets. This is not consistent with our expectation that increased liquidity reduces risk and therefore increases transaction prices, all else equal. A potential explanation is that our year fixed-effects are adequately controlling for time variation in market liquidity. Although not separately tabulated, the exclusion of *SAMEB*, *NOB*, *PRICEVOL*, and *LIQUIDITY* from the specifications increases the magnitude of the coefficients on *BF*, *SF*, *BE*, and *SC*.

The baseline results reported in Table 3 do not control for unobserved property characteristics as suggested by the model developed by Harding, Rosenthal and Sirmans (2003) and depicted in equation (10). In Table 4, we report results from estimating equation (10), our preferred model. As discussed above, the difference between *BF* and *SF* (*BF_SF_DIF*) captures the price effect related to distance from the transacted property for both the buyer and seller. Similarly, the difference between *BE* and *SC* (*BE_SC_DIF*) measures the price effect related to acquisitions by buyers from more expensive home markets and sellers from less expensive home markets. Finally, the difference between *BB* and *SB* (*BB_SB_DIF*) measures the price effect related to the use of brokerage services. The sum of *BF* and *SF* (*BF_SF_SUM*), the sum of *BE* and *SC* (*BE_SC_SUM*), and the sum of *BB* and *SB* (*BB_SB_SUM*) capture the price effects due to the unobserved characteristics of properties purchased and sold by these investors.

The key assumptions in this regression model are symmetry in the lack of bargaining power of distant buyers and sellers, symmetry in the anchoring bias of buyers from more expensive markets and sellers from less expensive markets, as well as symmetry in the effects of brokers on the sale prices paid and obtained by buyers and sellers. It is important to note that differencing and summing *BF* and *SF*, for example, as opposed to entering the two variables separately, adds no new information to the regression model.[9] Thus, the estimated coefficients on the remaining variables, as well as the regression R-squared, will be unchanged by the differencing and summing.

[9] This is because (BF-SF) + (BF+SF) + (BE-SC) + (BE+SC) = 2BF+2BE. However, the symmetry assumption implies that BF=SF and BE=SC. Thus, 2BF+2BE = BF+SF+BE+SC.

Table 4 reports bias corrected estimates using the Harding, Rosenthal and Sirmans (2003) approach. These regression results confirm our baseline findings that, on average, distant buyers pay price premiums when acquiring properties. However, relative to the results reported in Table 3, the estimated magnitude of the distant buyer price effect is reduced dramatically. For example, in Table 3 we report a coefficient estimate for *BF* of 0.2356 in the industrial property regression. However, in Table 4 the estimated coefficient on *BF_SF_DIF* in the industrial regression is 0.0953. The 0.1403 difference between these two coefficient estimates is equal to the estimated coefficient on *BF_SF_SUM*. Said differently, 0.1403 of the 0.2356 baseline coefficient estimate on *BF* reported in Table 3 is due to omitted variable bias, assuming the coefficient on *SF* is -1 times the coefficient on *BF* (the symmetry assumption among our distance variables). This substantial estimation bias is eliminated by the use of the "sums and differences" model. Similarly, the estimated coefficient on *BF* is reduced by 0.0785 in the multifamily model (0.1219 to 0.0434) and by 0.2647 (0.4020 to 0.1373) in the office market regression.

Use of the sums and differences model also reduces the measured effect of anchoring on prices. The estimated coefficient on *BE* reported in Table 3 is positive (0.0653) and significant (t-stat=7.40) in the office regression, indicating that buyers from more expensive home markets overpay for office properties. However, the estimated coefficient on *BE_SC_DIF* for office properties reported in the Table 4 is positive and significant, but reduced in magnitude by 0.0340 to a value of 0.0313. Assuming the coefficient on *SC* is -1 times the coefficient on *BE* (the symmetry assumption between our anchoring variables), approximately half of the estimated baseline impact of anchoring in the office sample is due to unobserved characteristics. These results again highlight the significant magnitude of the omitted variable bias in the baseline model estimates reported in Table 3. Similarly, the estimated price impacts of using a broker are significantly muted in the sums and differences model relative to the baseline model in the industrial and office sample. Nevertheless, we continue to find evidence that the use of a broker increases (decreases) sale prices for buyers (sellers).

Overall, our results suggest a distance price premium/discount that ranges between 4.4 percent for multifamily properties to 14.7 percent for office properties, an anchoring premium/discount that ranges from 0.6 percent for industrial to 3.5 percent for office properties, and a price premium/discount associated with the brokerage representation that ranges from 3 percent for industrial properties to 7.7 percent for office properties. The estimated anchoring effect using industrial properties appears to be negative. This could be due to a non-linear relationship between price differences and transaction prices. That is, the anchoring effect for industrial properties may be present only for large deviations in prices. We investigate this possibility later by allowing for a continuous relation between price differences and transaction prices.

In the regression results reported in Table 5, we add interaction variables between our distance and anchoring proxies and our same broker (*SAMEB*) and no broker (*NOB*) variables. The interactions of *BF_SF_DIF* with *SAMEB* is designed to test whether distant buyers pay incrementally more (and sellers receive less) when both parties to the transaction are represented by the same brokerage firm. The estimated coefficient on *SAMEB*BF_SF_DIF* cannot be distinguished from zero in any of the property type specifications, suggesting "dual" brokerage does not exacerbate the information disadvantage already faced by distance buyers and sellers. We also find no evidence that dual brokerage alters the effect of anchoring on sale prices.

The interactions of *BF_SF_DIF* with *NOB* reveal that the price premium paid by distant buyers and the discounts received by distant sellers of industrial and multifamily properties are significantly magnified if no broker is involved in the transaction. In contrast, the estimated coefficient on *BF_SF_DIF* in the office sample is decreased when no broker is involved in the transaction.

### *6.1 Robustness Checks*

The results reported in Table 4 and 5 assume the effects of distance and anchoring on negotiated sale prices can be captured with dichotomous (shift) variables. For example, the estimation model imposes the restriction that the effects of information asymmetries and search cost faced by buyers located 1,000 miles away from the acquired property are identical in magnitude to the disadvantages faced by buyers located 51 miles from the property. However, negotiated price effects may vary directly with distance or increase (decrease) in the relative expensiveness (cheapness) of the investor's home market.

In Table 6 we control for potential continuous distance effects by including *BDIST* and *SDIST*, which represent the distance in miles between the transacted property and the location of the buyer and the seller, respectively. Similarly, to capture potential anchoring effects that are continuous in the difference between prices in the investor's home market and prices in the transacted property's market, we also include *BPRICEDIF* and *SPRICEDIF*. *BPRICEDIF* (*SPRICEDIF*) is the difference in per square foot prices between the buyer's (seller's) home market and the transacted property's market.[10] We also allow for non-linearities in the effects of anchoring by including *BPRICEDIF2* and *SPRICEDIF2*, which are the square of *BPRICEDIF and* (*SPRICEDIF*), respectively.

[10] We winsorize *BPRICEDIF* and *SPRICEDIF* at the 0.1% level in each tail to eliminate outliers.

The results reported in Table 6 show that the estimated coefficient on *BF_SF_DIF* remains largely unchanged, suggesting a discontinuous price effect associated with distance. However, the estimated coefficients on both *BDIST* and *SDIST* are positive and highly significant in the industrial and office sample. The largest distance between a buyer/seller and a property in our sample is 2,700 miles. This implies that for the most distant buyers, the additional price premium increases to 42 percent [exp((2700*0.00005)-1)*100)].

Allowing for a continuous relation between sales prices and the price difference between the investor's local market and the property's market leads to an increase in the estimated coefficients on *BE_SC_DIF*. The significance of this coefficient further suggests that a common price effect related to anchoring exists in the multifamily and office markets. In addition, the coefficient in the industrial regression is no longer negative, confirming our earlier note that the observed negative coefficient on this variable in Tables 4 and 5 was due to a non-linear relationship between price difference and transaction price.

The estimated coefficients on *BPRICEDIF* and *BPRICEDIF2,* after controlling for *BE_SC_DIF*, suggest that the relationship between *BPRICEDIF* and price is weakly negative until the price difference is 382, 811, and 5 dollars/sqft, for industrial, multifamily and office markets, respectively; after which the relationship is positive.[11] The maximum observed price differences in the industrial, multi-family, and office samples are 500, 1000, and 800 dollars/sqft, respectively. These imply maximum additional price premiums of 76%, 81% and 0.6% for industrial, multi-family and office properties, respectively.

### *6.2 Summary of Estimated Price Effects*

Table 7 provides a summary of the various economic impacts from our baseline regression and augmented models. Using the baseline hedonic model, the results of which are reported in Table 3, we estimate that distant buyers in industrial markets pay an average price premium equal to 26.6 percent. However, when controlling for unobserved characteristics using the sums and differences model, the percentage price effect associated with distant buyers in the industrial market declines to 10.0 percent from 26.6 percent. In our office property sample, the percentage price impact declines from 49.5 percent in the baseline model to 14.7 percent in the sums and differences model. Clearly, the upward bias of the estimated distant buyer dummy variable associated with imperfect controls for unobserved characteristics can be large in magnitude.

[11] We obtain these inflection points by taking the first derivative of our price function with respect to price difference, setting it equal to zero, and solving for price difference. For example in the industrial equation, we obtain -0.00036 +9.43e-07*BPRICEDIF=0; BPRICEDIF=381.76.

The summary results reported in Table 7 also reveal the existence of an anchoring bias only in the office market. The upper bound of this bias is 6.8 percent in the office property sample (Panel A), while the lower bound is 3.5 percent (Panel B). In short, no matter the regression specification employed, the distance effect on price premiums is substantially and consistently stronger than the anchoring effect.

Looking at the broker effects, we find that office buyers pay 4.9 percent more and sellers receive 9.6 percent less without controlling for unobserved characteristics (Panel A). Controlling for unobserved characteristics (Panel B), the buyer premium and seller discount associated with using a broker is 7.7 percent. In the industrial and multifamily market, the buyer premium and seller discount is 3.0 percent and 4.0 percent respectively.

In Panel C we report the estimated percentage effects associated with distance, anchoring and use of intermediary when controlling for unobserved quality characteristics and the interaction effects of no brokerage (*NOB*) and dual brokerage (*SAMEB*) on distance and anchoring effects. The interpretation of the reported price effects associated with distant buyers and buyers from a more expensive market is that these are the price effects observed when the investors are not using the same brokerage firm, or any brokerage services. These price effects are similar to those reported in Panel B and vary from 2.6 percent (multifamily) to 16.4 percent (office) for distant buyers; 1.1 percent (multifamily) to 3.5 percent (office) for buyers from more expensive markets; and from 3.2 percent (industrial) to 7.7 percent (office) for buyers using brokerage services. The estimated price effects of no brokerage and dual brokerage can only be considered in association with the interaction effects of these variables with the distance and anchoring variables in this model.

## 7. Summary and Conclusions

Although the pricing of investments by distant versus local investors is likely to be affected by search costs, behavioral biases, and the use of information intermediaries, the relative importance of distance versus behavioral biases and the role of intermediaries has not been carefully examined in the existing literature. Using a large dataset of industrial, multifamily, and office property transactions that occurred during 1997-2011, we test for the effects of distance (search costs), behavioral biases, and information intermediary effects on commercial real estate pricing. CRE is an ideal testing ground to search for these effects because of the localized and segmented nature of CRE rental markets and the lack of liquidity and price transparency. Our research extends prior work by examining the role of search costs (i.e., information asymmetry and uncertainty), behavioral factors (i.e., anchoring), and the use of brokerage services on CRE pricing, controlling for unobserved property characteristics. In addition, we establish to what extent these effects vary by property type.

We find that distant buyers pay price premiums relative to local buyers across the fifteen largest US commercial real estate markets. These economically significant premiums exist in industrial, multifamily, and office property markets. In decomposing the sources of these price premiums, we find that search costs are both economically and statistically significant in explaining the observed price premiums; in contrast, behavioral biases in the form of anchoring effects tend to play a much more muted role. These results are confirmed with the use of more sophisticated econometric procedures that fully account for potential unobserved property characteristics correlated with investor attributes.

Finally, we find that the use of a broker significantly increases the acquisition prices of buyers and decreases the disposition prices of sellers. This result is inconsistent with the expectations of buyers and sellers who pay for brokerage services; however, it is consistent with the contention of Levitt and Syversun (2008) that brokers have an incentive to convince sellers to dispose of their properties too quickly. In contrast, "buyer" brokers encourage their principals to search less and therefore pay higher prices.

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## Table 1: Summary Statistics by Property Type

Summary statistics by property type for 34,755 industrial, 48,318 multi-family and 31,537 office property sales during 1997-2011. All variables are as defined in the Appendix. *BPRICEDIF* and *SPRICEDIF* are winsorized at the 0.1% at each tail of the distribution.

| Variable | Industrial Obs=34,733 | Multifamily Obs=48,318 | Office Obs=31,537 |
|---|---|---|---|
| Panel A: Summary Statistics of Property Structural Characteristics | | | |
| *PRICE* ($mils.) | 2.08 | 3.89 | 7.24 |
| *LNPRICE* | 14.15 | 14.30 | 14.46 |
| *AGE* (in yrs.) | 27.38 | 48.28 | 33.09 |
| *SQFT* (in thousands) | 38.23 | 39.50 | 38.26 |
| *LANDSF* (in thousands) | 137.16 | 107.38 | 85.84 |
| *UNITS* | N/A | 45.14 | N/A |
| *BDRMS1* | N/A | 15.62 | N/A |
| *BDRMS2* | N/A | 15.55 | N/A |
| *FLOORS* | 1.14 | 2.65 | 3.40 |
| *CLASSA* | 0.02 | N/A | 0.08 |
| *CLASSB* | 0.33 | N/A | 0.47 |
| *CLASSO* | 0.65 | N/A | 0.45 |
| *EXCEL* | 0.02 | 0.01 | 0.07 |
| *GOOD* | 0.12 | 0.09 | 0.21 |
| *ADEQ* | 0.46 | 0.74 | 0.42 |
| *NEEDSIMPR* | 0.04 | 0.03 | 0.02 |
| *POOR* | 0.00 | 0.01 | 0.00 |
| *NACOND* | 0.35 | 0.13 | 0.27 |
| *MASONRY* | 0.49 | 0.21 | 0.43 |
| *METAL* | 0.08 | 0.00 | 0.00 |
| *REINFCONCR* | 0.16 | 0.11 | 0.12 |
| *STEEL* | 0.02 | 0.01 | 0.07 |
| *WOOD* | 0.02 | 0.23 | 0.08 |
| *NAMATERIAL* | 0.23 | 0.44 | 0.30 |
| *AVALUE* | 1.23 | 2.00 | 3.91 |
| *NAAVALUE* | 0.15 | 0.07 | 0.19 |
| Panel B: Summary Statistics for Sample Distribution by Year | | | |
| | Industrial | Multifamily | Office |
| *1997* | 0.04 | 0.04 | 0.04 |
| *1998* | 0.05 | 0.06 | 0.05 |
| *1999* | 0.05 | 0.06 | 0.05 |
| *2000* | 0.06 | 0.07 | 0.06 |
| *2001* | 0.06 | 0.07 | 0.05 |
| *2002* | 0.07 | 0.09 | 0.06 |
| *2003* | 0.08 | 0.10 | 0.08 |
| *2004* | 0.11 | 0.13 | 0.10 |
| *2005* | 0.12 | 0.12 | 0.12 |
| *2006* | 0.12 | 0.09 | 0.13 |
| *2007* | 0.10 | 0.06 | 0.11 |
| *2008* | 0.06 | 0.04 | 0.07 |
| *2009* | 0.03 | 0.02 | 0.03 |
| *2010* | 0.04 | 0.03 | 0.03 |
| *2011* | 0.01 | 0.01 | 0.01 |

## Table 1: Summary Statistics by Property Type (continued)

Panel C: Mean Values of Distance, Anchoring, Broker, Price Volatility, and Market Liquidity Proxies

| | Industrial | Multifamily | Office |
|---|---|---|---|
| *BF* | 0.10 | 0.12 | 0.11 |
| *SF* | 0.14 | 0.13 | 0.13 |
| *BDIST* | 88.44 | 100.20 | 93.38 |
| *SDIST* | 110.03 | 100.95 | 108.73 |
| *BE* | 0.23 | 0.31 | 0.26 |
| *SC* | 0.77 | 0.71 | 0.73 |
| *BPRICEDIF* | 5.61 | 21.98 | 11.83 |
| *SPRICEDIF* | 5.18 | 17.30 | 10.75 |
| *BB* | 0.34 | 0.36 | 0.30 |
| *SB* | 0.47 | 0.45 | 0.47 |
| *SAMEB* | 0.14 | 0.21 | 0.13 |
| *NOB* | 0.49 | 0.50 | 0.49 |
| *PRICEVOL* | 41.61 | 64.55 | 44.25 |
| *LIQUIDITY* | 361.79 | 653.51 | 251.21 |

## Table 2: Pairwise Correlations between the Main Variables Used in the Regression Analysis

Pairwise correlations between the main variables used in the regression analysis in 114,588 property sales during 1997-2011. All variables are as defined in the Appendix. * indicates significance at the 10% level or better.

| | *LN PRICE* | *AGE* | *SQFT* | *LAND SF* | *BF* | *SF* | *BE* | *SC* | *BB* | *SB* | *BF_SF_ DIF* | *BF_SF_ SUM* | *BE_SC_ DIF* | *BE_SC_ SUM* | *BB_SB_ DIF* | *BB_SB_ SUM* | *SAMEB* | *NOB* | *PRICE VOL* | *LIQUI DITY* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *LNPRICE* | 1.0000 | | | | | | | | | | | | | | | | | | | |
| *AGE* | -0.0949* | 1.0000 | | | | | | | | | | | | | | | | | | |
| *SQFT* | 0.6604* | -0.1207* | 1.0000 | | | | | | | | | | | | | | | | | |
| *LANDSF* | 0.0363* | -0.0159* | 0.0522* | 1.0000 | | | | | | | | | | | | | | | | |
| *BF* | 0.3353* | -0.1316* | 0.2976* | 0.0213* | 1.0000 | | | | | | | | | | | | | | | |
| *SF* | 0.2229* | -0.1008* | 0.2131* | 0.0157* | 0.2079* | 1.0000 | | | | | | | | | | | | | | |
| *BE* | 0.1180* | -0.0149* | 0.1119* | 0.0065* | 0.2019* | 0.0637* | 1.0000 | | | | | | | | | | | | | |
| *SC* | -0.0737* | 0.0249* | -0.0865* | -0.0023 | -0.0680* | -0.1445* | -0.1593* | 1.0000 | | | | | | | | | | | | |
| *BB* | 0.0602* | -0.0097* | -0.0142* | -0.0075* | 0.0142* | 0.0214* | 0.0400* | -0.0308* | 1.0000 | | | | | | | | | | | |
| *SB* | 0.1164* | -0.0383* | 0.0457* | -0.0029 | 0.0487* | 0.0527* | 0.0525* | -0.0439* | 0.5893* | 1.0000 | | | | | | | | | | |
| *BF_SF_DIF* | 0.0730* | -0.0177* | 0.0522* | 0.0034 | 0.5936* | -0.6638* | 0.1020* | 0.0668* | -0.0067* | -0.0061* | 1.0000 | | | | | | | | | |
| *BF_SF_SUM* | 0.3563* | -0.1487* | 0.3264* | 0.0236* | 0.7582* | 0.7955* | 0.1676* | -0.1385* | 0.0230* | 0.0653* | -0.0748* | 1.0000 | | | | | | | | |
| *BE_SC_DIF* | 0.1260* | -0.0261* | 0.1303* | 0.0058* | 0.1775* | 0.1366* | 0.7624* | -0.7603* | 0.0466* | 0.0633* | 0.0233* | 0.2010* | 1.0000 | | | | | | | |
| *BE_SC_SUM* | 0.0345* | 0.0076* | 0.0199* | 0.0032 | 0.1037* | -0.0620* | 0.6500* | 0.6466* | 0.0072* | 0.0068* | 0.1303* | 0.0229* | 0.0038 | 1.0000 | | | | | | |
| *BB_SB_DIF* | -0.0671* | 0.0330* | -0.0670* | -0.0048 | -0.0399* | -0.0367* | -0.0164* | 0.0165* | 0.4065* | -0.4986* | -0.0003 | -0.0492* | -0.0216* | 0.0001 | 1.0000 | | | | | |
| *BB_SB_SUM* | 0.0999* | -0.0273* | 0.0185* | -0.0057* | 0.0358* | 0.0420* | 0.0521* | -0.0421* | 0.8853* | 0.8974* | -0.0072* | 0.0502* | 0.0618* | 0.0078* | -0.0650* | 1.0000 | | | | |
| *SAMEB* | 0.0794* | 0.0163* | 0.0169* | -0.0042 | 0.0333* | 0.0234* | 0.0511* | -0.0315* | 0.6249* | 0.4825* | 0.0062* | 0.0363* | 0.0543* | 0.0152* | 0.1248* | 0.6190* | 1.0000 | | | |
| *NOB* | -0.1219* | 0.0438* | -0.0485* | 0.0034 | -0.0489* | -0.0531* | -0.0531* | 0.0447* | -0.7083* | -0.9173* | 0.0063* | -0.0657* | -0.0643* | -0.0066* | 0.2774* | -0.9147* | -0.4426* | 1.0000 | | |
| *PRICEVOL* | 0.1603* | 0.0109* | 0.4486* | 0.1350* | 0.0412* | 0.0349* | 0.0322* | -0.0200* | 0.0357* | -0.002 | 0.0028 | 0.0488* | 0.0343* | 0.0094* | 0.0402* | 0.0185* | 0.0694* | 0.0027 | 1.0000 | |
| *LIQUIDITY* | -0.0980* | 0.0535* | -0.0894* | -0.0118* | -0.0767* | -0.0736* | 0.0581* | -0.0416* | 0.1049* | 0.0852* | 0.0018 | -0.0966* | 0.0655* | 0.0129* | 0.0162* | 0.1063* | 0.0752* | -0.0967* | 0.1417* | 1.0000 |

## Table 3: Baseline Hedonic Regression Model

Regression estimates by property type for 114,588 property sales during 1997-2011. The dependent variable is the natural log of the sale price. All variables are defined in the Appendix. Standard errors are corrected for potential heteroskedasticity. Estimated coefficients on sub-property types and sub-markets are absorbed for brevity. T-statistics are reported in the parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent level, respectively.

| | Industrial Obs = 34,733 | | Multi-family Obs = 48,318 | | Office Obs = 31,537 | |
|---|---|---|---|---|---|---|
| **Variables** | Coef. | T-stat | Coef. | T-stat | Coef. | T-stat |
| *BF* | 0.2356*** | (20.32) | 0.1219*** | (11.47) | 0.4020*** | (27.05) |
| *SF* | 0.0450*** | (5.03) | 0.0350*** | (3.86) | 0.1274*** | (9.84) |
| *BE* | 0.0002 | (0.03) | 0.0034 | (0.62) | 0.0653*** | (7.40) |
| *SC* | 0.0381*** | (5.62) | -0.0095* | (-1.76) | 0.0028 | (0.33) |
| *BB* | 0.0638*** | (7.01) | 0.0303*** | (3.16) | 0.0474*** | (3.73) |
| *SB* | 0.0040 | (0.26) | -0.0474*** | (-3.72) | -0.1010*** | (-4.97) |
| *SAMEB* | -0.0095 | (-0.97) | 0.1051*** | (11.82) | 0.0587*** | (4.11) |
| *NOB* | -0.0197 | (-1.14) | -0.0644*** | (-4.37) | -0.1451*** | (-6.46) |
| *PRICEVOL* | -0.0001*** | (-4.14) | -0.0000* | (-1.82) | -0.0005*** | (-9.92) |
| *LIQUIDITY* | -0.0019*** | (-3.76) | -0.0005 | (-0.88) | -0.0028*** | (-12.30) |
| *AVALUE* | 0.0089 | (1.43) | -0.0091*** | (-20.61) | 0.0016* | (1.73) |
| *NAVALUE* | -0.0902*** | (-9.26) | 0.0144*** | (5.96) | -0.2702*** | (-22.70) |
| *AGE* | -0.0057*** | (-12.92) | -0.0508*** | (-3.05) | -0.0029*** | (-7.72) |
| *AGE2* | 0.0000*** | (3.88) | 0.0000*** | (9.32) | 0.0000*** | (3.18) |
| *SQFT* | 0.0088*** | (38.79) | 0.0070*** | (11.20) | 0.0109*** | (39.24) |
| *SQFT2* | -0.0000*** | (-5.63) | -0.0000*** | (-5.11) | -0.0000*** | (-8.23) |
| *LANDSF* | 0.0001*** | (3.36) | -0.0000 | (-0.53) | 0.0001 | (1.14) |
| *LANDSF2* | -0.0000*** | (-4.25) | 0.0000 | (1.00) | -0.0000 | (-0.95) |
| *UNITS* | | | 0.0025*** | (4.84) | | |
| *BDRMS1* | | | 0.0002 | (0.42) | | |
| *BDRMS2* | | | 0.0010*** | (3.04) | | |
| *FLOORS* | 0.0113 | (1.30) | 0.0368*** | (8.17) | -0.0103*** | (-3.88) |
| *CLASSA* | -0.0162 | (-0.54) | | | 0.5454*** | (19.71) |
| *CLASSB* | 0.0866*** | (12.57) | | | 0.2828*** | (30.87) |
| *NACOND* | 0.0232*** | (3.28) | 0.0601*** | (7.20) | 0.0335*** | (3.40) |
| *EXCEL* | 0.0677*** | (2.80) | 0.1730*** | (5.07) | 0.0833*** | (3.35) |
| *GOOD* | 0.0079 | (0.77) | 0.1423*** | (13.34) | 0.1186*** | (10.30) |
| *NEEDSIMPR* | -0.0571*** | (-4.22) | -0.0482*** | (-3.18) | -0.0503** | (-2.36) |
| *POOR* | -0.0779 | (-1.64) | -0.0944*** | (-4.05) | 0.1946*** | (2.89) |
| *NAMATERIAL* | -0.0323*** | (-4.31) | -0.0363*** | (-4.66) | -0.0195** | (-2.09) |
| *METAL* | -0.0490*** | (-4.71) | 0.0436 | (0.26) | -0.0191 | (-0.28) |
| *REINFCONCR* | 0.0416*** | (4.59) | 0.0202 | (1.60) | 0.0571*** | (4.07) |
| *STEEL* | -0.0171 | (-0.97) | 0.1092*** | (2.61) | 0.1629*** | (8.22) |
| *WOOD* | -0.1620*** | (-6.95) | -0.0348*** | (-3.80) | -0.1636*** | (-12.30) |
| *LONG* | 0.0905*** | (4.77) | 0.2298*** | (3.41) | -0.0443** | (-2.30) |
| *LAT* | 0.4118*** | (5.60) | 0.5948*** | (7.00) | -0.2353*** | (-3.07) |
| *1998* | -0.0494** | (-2.53) | -0.0031 | (-0.15) | -0.0949*** | (-3.54) |
| *1999* | -0.0152 | (-0.75) | 0.0449** | (2.10) | -0.1023*** | (-3.82) |
| *2000* | 0.0319 | (1.62) | 0.1176*** | (5.46) | -0.0384 | (-1.46) |
| *2001* | 0.0986*** | (5.04) | 0.1588*** | (7.37) | -0.0154 | (-0.59) |
| *2002* | 0.1118*** | (5.79) | 0.2234*** | (10.39) | -0.0112 | (-0.43) |
| *2003* | 0.1392*** | (7.07) | 0.3117*** | (14.30) | 0.0355 | (1.39) |
| *2004* | 0.2277*** | (11.35) | 0.4334*** | (19.50) | 0.1855*** | (7.11) |
| *2005* | 0.3666*** | (18.14) | 0.5751*** | (26.48) | 0.3054*** | (11.31) |
| *2006* | 0.4158*** | (20.03) | 0.6159*** | (28.55) | 0.3340*** | (11.96) |
| *2007* | 0.4328*** | (20.83) | 0.6007*** | (27.51) | 0.2536*** | (9.64) |
| *2008* | 0.3680*** | (17.58) | 0.5512*** | (23.24) | 0.1179*** | (4.43) |
| *2009* | 0.2359*** | (10.37) | 0.4096*** | (15.89) | -0.0625** | (-2.06) |
| *2010* | 0.2079*** | (9.65) | 0.4174*** | (16.99) | -0.1186*** | (-4.03) |
| *2011* | 0.1879*** | (6.85) | 0.4774*** | (16.56) | -0.0710* | (-1.74) |
| *CONST* | 7.7982*** | (5.06) | 16.3242** | (2.25) | 18.4394*** | (15.29) |
| *Sub-property type dummies* | yes | | not applicable | | yes | |
| *Sub-market dummies* | yes | | yes | | yes | |
| *R-squared* | 0.599 | | 0.755 | | 0.751 | |

## Table 4: Controlling for Unobserved Characteristics

Regression estimates by property type for 114,588 property sales during 1997-2011. The dependent variable is the natural log of the sale price. All variables are defined in the Appendix. Standard errors are corrected for potential heteroskedasticity. Estimated coefficients on the constant, structural characteristics, longitude, latitude, year fixed effects, sub-property types and sub-markets are absorbed for brevity. T-statistics are reported in the parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent level, respectively.

| | Industrial Obs = 34733 | | Multi-family Obs = 48,318 | | Office Obs = 31,537 | |
|---|---|---|---|---|---|---|
| Variables | Coef. | T-stat | Coef. | T-stat | Coef. | T-stat |
| *BF_SF_DIF* | 0.0953*** | (13.01) | 0.0434*** | (6.25) | 0.1373*** | (15.41) |
| *BF_SF_SUM* | 0.1403*** | (19.18) | 0.0785*** | (11.19) | 0.2647*** | (31.68) |
| *BE_SC_DIF* | -0.0190*** | (-4.00) | 0.0064* | (1.74) | 0.0313*** | (5.48) |
| *BE_SC_SUM* | 0.0191*** | (3.84) | -0.0031 | (-0.78) | 0.0341*** | (5.36) |
| *BB_SB_DIF* | 0.0299*** | (3.84) | 0.0389*** | (6.13) | 0.0742*** | (7.82) |
| *BB_SB_SUM* | 0.0339*** | (3.36) | -0.0086 | (-0.92) | -0.0268* | (-1.93) |
| *SAMEB* | -0.0095 | (-0.97) | 0.1051*** | (11.82) | 0.0587*** | (4.07) |
| *NOB* | -0.0197 | (-1.14) | -0.0644*** | (-4.37) | -0.1451*** | (-6.58) |
| *PRICEVOL* | -0.0001*** | (-4.14) | -0.0000* | (-1.82) | -0.0005*** | (-9.82) |
| *LIQUIDITY* | -0.0019*** | (-3.76) | -0.0005 | (-0.88) | -0.0028*** | (-45.42) |
| *Sub-property type dummies* | yes | | not applicable | | yes | |
| *Sub-market dummies* | yes | | yes | | yes | |
| *R-squared* | 0.599 | | 0.755 | | 0.751 | |

## Table 5: Controlling for Unobserved Characteristics and Broker Interaction Effects

Regression estimates by property type for 114,588 property sales during 1997-2011. The dependent variable is the natural log of the sale price. All variables are defined in the Appendix. Standard errors are corrected for potential heteroskedasticity. Estimated coefficients on the constant, structural characteristics, longitude, latitude, year fixed effects, sub-property types and sub-markets are absorbed for brevity. T-statistics are reported in the parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent level, respectively.

| | Industrial Obs = 34733 | | Multifamily Obs = 48,318 | | Office Obs = 31,537 | |
|---|---|---|---|---|---|---|
| **Variables** | Coef. | T-stat | Coef. | T-stat | Coef. | T-stat |
| *BF_SF_DIF* | 0.0641*** | (5.86) | 0.0255** | (2.04) | 0.1521*** | (10.07) |
| *BF_SF_SUM* | 0.0940*** | (8.53) | 0.0625*** | (5.70) | 0.2584*** | (18.45) |
| *BE_SC_DIF* | -0.0083 | (-1.13) | 0.0107* | (1.66) | 0.0381*** | (4.16) |
| *BE_SC_SUM* | 0.0207*** | (2.68) | 0.0085 | (1.18) | 0.0422*** | (4.18) |
| *BB_SB_DIF* | 0.0312*** | (4.01) | 0.0381*** | (6.01) | 0.0741*** | (7.52) |
| *BB_SB_SUM* | 0.0331*** | (3.29) | -0.0097 | (-1.04) | -0.0268* | (-1.95) |
| *SAMEB* | -0.0376* | (-1.90) | 0.1200*** | (7.88) | 0.0725*** | (2.67) |
| *NOB* | -0.0415** | (-1.98) | -0.0611*** | (-3.44) | -0.1426*** | (-5.29) |
| *PRICEVOL* | -0.0001*** | (-4.06) | -0.0000* | (-1.79) | -0.0005*** | (-9.90) |
| *LIQUIDITY* | -0.0019*** | (-3.76) | -0.0005 | (-0.88) | -0.0028*** | (-12.34) |
| *SAMEB*BF_SF_DIF* | 0.0251 | (1.24) | 0.0072 | (0.41) | 0.0301 | (1.09) |
| *SAMEB*BF_SF_SUM* | 0.0716*** | (3.65) | 0.0401*** | (2.72) | 0.0300 | (1.21) |
| *SAMEB*BE_SC_DIF* | 0.0020 | (0.14) | 0.0028 | (0.28) | 0.0040 | (0.23) |
| *SAMEB*BE_SC_SUM* | 0.0118 | (0.80) | -0.0239** | (-2.13) | -0.0203 | (-0.98) |
| *NOB*BF_SF_DIF* | 0.0579*** | (3.65) | 0.0356** | (2.25) | -0.0490** | (-2.25) |
| *NOB*BF_SF_SUM* | 0.0724*** | (5.03) | 0.0147 | (1.13) | 0.0028 | (0.15) |
| *NOB*BE_SC_DIF* | -0.0227** | (-2.25) | -0.0096 | (-1.19) | -0.0156 | (-1.29) |
| *NOB*BE_SC_SUM* | -0.0072 | (-0.66) | -0.0123 | (-1.33) | -0.0119 | (-0.87) |
| *Sub-property type dummies* | yes | | not applicable | | yes | |
| *Sub-market dummies* | yes | | yes | | yes | |
| *R-squared* | 0.599 | | 0.756 | | 0.751 | |

## Table 6: Distance and Non-Linear Robustness Checks

Regression estimates by property type for 114,588 property sales during 1997-2011. The dependent variable is the natural log of the sale price. All variables are defined in the Appendix. Standard errors are corrected for potential heteroskedasticity. Estimated coefficients on the constant, structural characteristics, longitude, latitude, year fixed effects, sub-property types and sub-markets are absorbed for brevity. T-statistics are reported in the parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent level, respectively.

| | Industrial Obs = 34733 | | Multifamily Obs = 48,318 | | Office Obs = 31,537 | |
|---|---|---|---|---|---|---|
| **Variables** | Coef. | T-stat | Coef. | T-stat | Coef. | T-stat |
| *BF_SF_DIF* | 0.0635*** | (4.97) | 0.0210 | (1.54) | 0.1503*** | (8.42) |
| *BF_SF_SUM* | 0.0242* | (1.94) | 0.0567*** | (4.60) | 0.1940*** | (11.56) |
| *BE_SC_DIF* | 0.0050 | (0.63) | 0.0359*** | (4.87) | 0.0610*** | (6.04) |
| *BE_SC_SUM* | 0.0185** | (2.19) | 0.0193** | (2.36) | 0.0542*** | (4.89) |
| *BB_SB_DIF* | 0.0315*** | (4.08) | 0.0380*** | (6.00) | 0.0743*** | (7.58) |
| *BB_SB_SUM* | 0.0335*** | (3.33) | -0.0107 | (-1.15) | -0.0274** | (-1.99) |
| *SAMEB* | -0.0380* | (-1.92) | 0.1202*** | (7.88) | 0.0726*** | (2.68) |
| *NOB* | -0.0419** | (-2.00) | -0.0628*** | (-3.55) | -0.1435*** | (-5.34) |
| *PRICEVOL* | -0.0001*** | (-4.24) | -0.0000* | (-1.91) | -0.0005*** | (-9.80) |
| *LIQUIDITY* | -0.0019*** | (-3.77) | -0.0005 | (-0.88) | -0.0028*** | (-12.38) |
| *BDIST* | 0.0001*** | (6.21) | 0.0000 | (0.83) | 0.0001*** | (3.59) |
| *SDIST* | 0.0001*** | (7.81) | 0.0000 | (0.16) | 0.0001*** | (4.18) |
| *BPRICEDIF* | -0.0004*** | (-3.52) | -0.0004*** | (-6.51) | -0.0003*** | (-5.23) |
| *BPRICEDIF2* | 0.0000*** | (3.09) | 0.0000*** | (4.46) | 0.0000*** | (3.28) |
| *SPRICEDIF* | -0.0005*** | (-5.30) | -0.0002*** | (-2.69) | -0.0002*** | (-2.69) |
| *SPRICEDIF2* | 0.0000*** | (5.29) | 0.0000*** | (3.71) | 0.0000*** | (3.74) |
| *SAMEB*BF_SF_DIF* | 0.0271 | (1.35) | 0.0076 | (0.43) | 0.0359 | (1.30) |
| *SAMEB*BF_SF_SUM* | 0.0708*** | (3.64) | 0.0396*** | (2.68) | 0.0354 | (1.42) |
| *SAMEB*BE_SC_DIF* | 0.0028 | (0.20) | 0.0022 | (0.22) | 0.0016 | (0.09) |
| *SAMEB*BE_SC_SUM* | 0.0113 | (0.76) | -0.0231** | (-2.05) | -0.0208 | (-1.01) |
| *NOB*BF_SF_DIF* | 0.0567*** | (3.61) | 0.0362** | (2.29) | -0.0468** | (-2.17) |
| *NOB*BF_SF_SUM* | 0.0655*** | (4.58) | 0.0138 | (1.06) | 0.0094 | (0.52) |
| *NOB*BE_SC_DIF* | -0.0215** | (-2.14) | -0.0117 | (-1.43) | -0.0171 | (-1.42) |
| *NOB*BE_SC_SUM* | -0.0065 | (-0.60) | -0.0129 | (-1.40) | -0.0132 | (-0.96) |
| *Sub-property type dummies* | yes | | not applicable | | yes | |
| *Sub-market dummies* | yes | | yes | | yes | |
| *R-squared* | 0.602 | | 0.756 | | 0.752 | |

## Table 7: Economic Impact of Distant Buyers and Buyers from More Expensive Markets

This table presents the estimated price effects related to distance and anchoring during 1997-2011, estimated by property type. Panel A reports the price effects based on the coefficient estimates reported in Table 3 using a baseline hedonic pricing model where the dependent variable is the natural log of the sale price and an indicator variable approach is employed to isolate the price premium or discount related to distant buyer/seller and buyer (seller) from a more expensive (cheaper) market. Panel B reports the price effects based on the coefficient estimates reported in Table 4, where the dependent variable is again the natural log of the sale price and where we control for unobserved characteristics to distinguish between the effect associated with distant buyer/seller, buyer (seller) from a more expensive (cheaper) market, buyer(seller) using a broker and the effect related to unobserved property characteristics that are correlated with distant investors, investors from cheaper/more expensive markets, investors using a broker. Panel C reports the price effects based on the coefficient estimates reported in Table 5, where the dependent variable is the natural log of the sale price and in addition for controlling for unobserved characteristics we also control for interaction effects between No Broker/Dual Broker and Distant Buyer (Seller)/Buyer from a More Expensive Market (Seller from a Cheaper Market).

| | Industrial<br>Obs = 34733 | Multifamily<br>Obs = 48,318 | Office<br>Obs = 31,537 |
|---|---|---|---|
| *Panel A: Basic Hedonic Model Specification (based on Table 3)* | | | |
| Distant Buyer | 26.6% | 13.0% | 49.5% |
| Distant Seller | 4.6% | 3.6% | 13.6% |
| Buyer from a More Expensive Market | n.s. | n.s. | 6.8% |
| Seller from a Cheaper Market | 3.9% | -1.0% | n.s. |
| Buyer using a Broker | 6.6% | 3.1% | 4.9% |
| Seller using a Broker | n.s. | -4.6% | -9.6% |
| No Broker Involved | n.s. | -6.2% | -13.5% |
| Dual Brokerage | n.s. | 11.1% | 6.1% |
| *Panel B: Hedonic Model Controling for Unobserved Characteristics (based on Table 4)* | | | |
| Distant Buyer (=-Distant Seller) | 10.0% | 4.4% | 14.7% |
| Buyer from a More Expensive Market (=-Seller from a Cheaper Mar | -1.9% | 0.6% | 3.5% |
| Buyer using a Broker (=-Seller using a Broker) | 3.0% | 4.0% | 7.7% |
| No Broker Involved | n.s. | -6.2% | -13.5% |
| Dual Brokerage | n.s. | 11.1% | 6.1% |
| *Panel C: Hedonic Model Controling for Unobserved Characteristics and Interaction Effects between No Broker/Dual Broker and Distant Buyer (Seller)/Buyer from a More Expensive Market (Seller from a Cheaper Market) (based on Table 5)* | | | |
| Distant Buyer (=-Distant Seller) | 6.6% | 2.6% | 16.4% |
| Buyer from a More Expensive Market (=-Seller from a Cheaper Mar | n.s. | 1.1% | 3.5% |
| Buyer using a Broker (=-Seller using a Broker) | 3.2% | 3.9% | 7.7% |
| No Broker Involved | -4.4% | -5.9% | -13.3% |
| Dual Brokerage | -3.7% | 12.8% | 7.5% |

## Appendix: Variable Definitions

| Variable | Definition |
|---|---|
| *PRICE* | Nominal sale price in million USD |
| *LNPRICE* | Natural logarithm of the sale price in USD |
| *AVALUE* | Assessed value of the asset for property tax purposes in million USD |
| *NAVALUE* | Indicator variable denoting a missing assessed value for the given property |
| *AGE* | Age of the property in years |
| *SQFT* | Total square footage of improvements in thousand square feet |
| *SQFT2* | The square of *SQFT* |
| *LANDSF* | Land square footage in thousand square feet |
| *LANDSF2* | The square of *LANDSQFT* |
| *UNITS* | Number of apartment units in the building |
| *BDRMS1* | Number of one-bedroom units in the apartment property |
| *BDRMS2* | Number of two-bedroom units in the apartment property |
| *FLOORS* | Number of floors in the apartment property |
| $CLASS_j$ | Indicator variable denoting class; *A* and *B* denote Class A and Class B properties, respectively. *O* denotes a property rated as a Class C property or lower. |
| $COND_j$ | Indicator variable denoting property condition; *NA, EXCL*, *GOOD*, *NEEDSIMPR*, *POOR* denote missing, excellent, good, needs improvements and poor condition, respectively. The omitted condition is adequate, ADEQ. |
| $MATERIAL_j$ | Indicator variable denoting primary construction material; *NA*, *METAL*, *REINFCONCR*, *STEEL*, and *WOOD* denote missing, metal, reinforced concrete, steel, and wood as main construction material of the structure, respectively. The omitted material is *MASONRY*. |
| $YR_n$ | Indicator variables for each sale year: 1998-2011. The omitted year is 1997 |
| *BDIST* | Distance in miles between the buyer's listed address and the property |
| *SDIST* | Distance in miles between the seller's listed address and the property on the seller's and the property indicated addresses |
| *BF* | Variable indicating a distant buyer; set equal to one if the buyer's address is 50 miles or further from the property's address |
| *SF* | Variable indicating a distant seller; set equal to one if the seller's address is 50 miles or further from the property's address |
| *BPRICEDIF* | The difference in median price per square foot between the buyer's home market (based on his address) and the market in which the transacted property is located; *BPRICEDIF* is winsorized at the 0.1% at each tail. |
| *SPRICEDIF* | The difference in median price per square foot between the seller's home market (based on his address) and the transacted property's market; *SPRICEDIF* is winsorized at the 0.1% at each tail. |
| *BE* | Variable indicating buyer is from a relatively expensive market; set equal to one if the median price per square foot in the buyer's home market is greater than the median price per square foot observed in the transacted property's market; calculated by property type. |
| *SC* | Variable indicating seller is from a relatively inexpensive market; set equal to one if median price per square foot in the seller's home market is less than median price per square foot observed in the transacted property's market; calculated by property type. |

| | |
|---|---|
| *BB* | A category variable set equal to one if buyer is represented by a broker. |
| *SB* | A category variable set equal to one if seller buyer is represented by a broker. |
| *SAMEB* | An indicator variable set equal to one if seller and buyer were represented by the same brokerage firm. |
| *NOB* | An indicator variable set equal to one if neither the seller nor buyer were represented by a broker; includes observations with no information on the use of brokers. |
| *LIQUIDITY* | Number of transactions by year, by property type and zip code. |
| *PRICEVOL* | Square of the residual from a hedonic regression by property type, year and zip code, using the standard structural characteristics, and controlling for property location |
| *LONG* | Longitude coordinate of the property |
| *LAT* | Latitude coordinate of the property |
| *AVALUE* | Assessed value of property for property tax purposes. |