

A Comprehensive Approach to Commercial Real Estate Prices¹

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ABSTRACT

The CRE market is characterized by heterogeneity and a high degree of segmentation, creating a challenge for developing a comprehensive CRE price index. Existing indices in the market place have primarily focused on high-value transactions — a small fraction of total CRE transactions. To capture the multifaceted and diverse picture of the CRE market, we explored alternative repeat-sale indexing methodologies to determine the most appropriate approach. We found that conventional methods using prices as breakpoints for determining market tiers produced biased indices. Our indices were thus developed based on datasets defined by physical characteristics of properties. We concluded that using a consistent indexing methodology to track mutually exclusive market segments is the most accurate, straightforward, and comprehensive approach.

I. BACKGROUND

The CoStar Commercial Repeat-Sale Index (CCRSI) was developed by using the repeat-sale regression technique, which has been increasingly accepted as the most clear-cut and sufficiently rigorous method to meet investors' requirements. The repeat-sale analysis, based on properties that have sold more than once without any significant change in building characteristics between sales, is fundamentally comparable to stock and bond indices, which are based on stock (or bond) price changes from one period to the next. In real estate, the most well-known repeat-sale index is the Standard & Poor's Case-Shiller Home Price Index. Not only has the Case-Shiller Index become the barometer of the health of the nation's housing market, it has also been used by the Chicago Mercantile Exchange to support and facilitate derivatives trading against housing. OFHEO's Home Price Index is another example of a repeat-sale-based index that has been widely used and cited in the residential housing market.

In the CRE market place, the most commonly used price index to date is the one produced by the National Council of Real Estate Investments Fiduciaries (NCREIF). The NCREIF Index is appraisal-based rather than transaction-based and is derived from a small data sample that consists solely of large and prime properties owned by pension fund investors. The Moody's/Real CPPI was the first CRE repeat-sale index, developed in 2007. However, the use of this index is limited by the lack of comprehensive data coverage. CPPI is based on transaction data from Real Capital Analytics (RCA), which has approximately 10 years of history and focuses only on high-value transactions. RCA data initially covered transactions of \$5 million-up and extended to \$2.5 million-up in 2005.

CoStar began collecting CRE transaction data 20 years ago and has a total of 1.33 million CRE property sales records in its database. It covers CRE transactions across the United States in all price ranges. This extensive database with a long history contains a large number of repeat transactions from which we were able to develop consistent and comprehensive price indices.

II. DATA & FEATURE EXTRACTION

Accurate identification of repeat-sale pairs is critical to building an accurate index that reflects market conditions excluding all other non-market factors. We therefore applied three stages of filtering to the CoStar transaction database to obtain the final sales pairs. In the first stage, we extracted a dataset containing properties that were sold more than once. We compared multiple building characteristics to ensure that two transactions were indeed the same asset. In the second stage, we set up 32 exclusionary criteria to filter out non-representative transactions, such as portfolio sales, non-arm’s-length transactions, and build-to-suit transactions. Also excluded were properties below a minimum physical threshold of square footage and units.

The third stage of data filtering mainly targeted “flippers” — those properties sold more than once within a short period of time — and “outliers,” properties with abnormal price increases. Both were identified empirically. As Chart 1 shows, most transactions occurred after a 12-month holding period, which is consistent with generally accepted practice because of U.S. tax considerations. Therefore, transactions occurring in less than a 12-month period are filtered out as “flippers.”

CHART 1

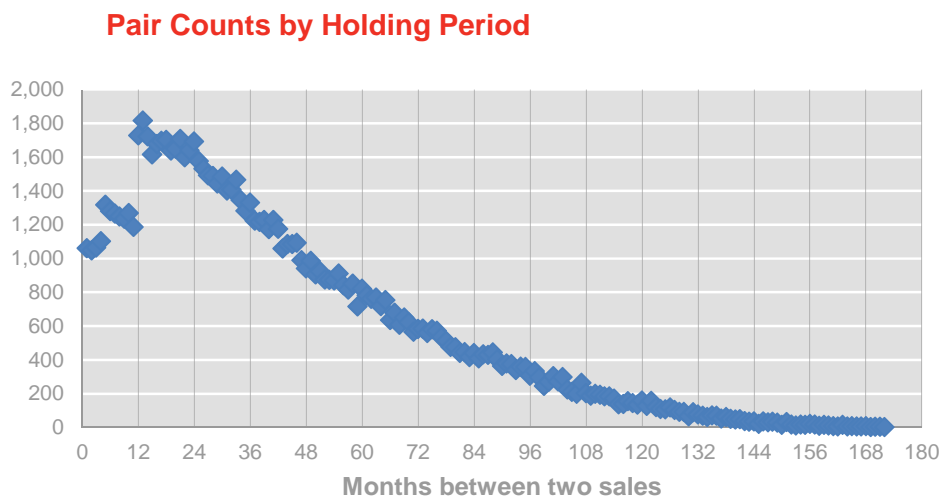
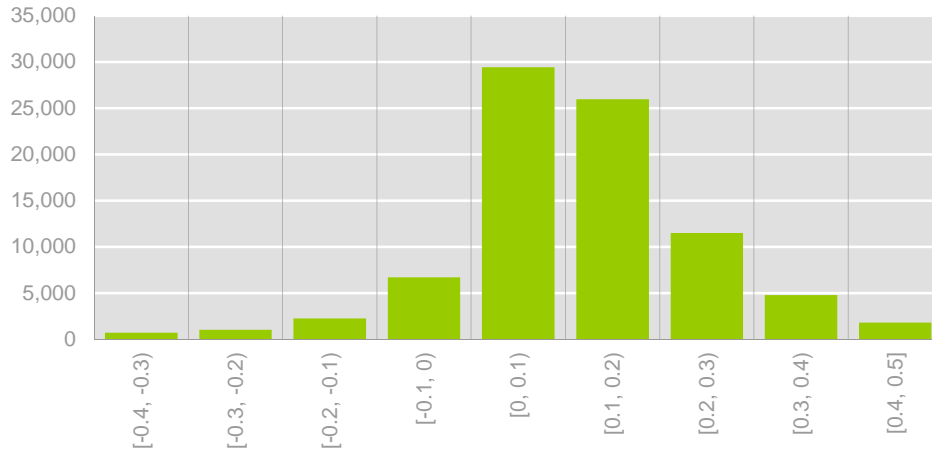


Chart 2 shows pair distribution by the average annual price change. Most of the pairs cluster around the 10% to 20% range. The pair counts decrease quickly in both directions. Roughly 98% of the total pairs fall into the range between -40% and 50%. We thus excluded the pairs at the extreme ends of the spectrum as “outliers” for all property types except for land. The range for land is -50% to 60% because it has a much wider and flatter distribution.

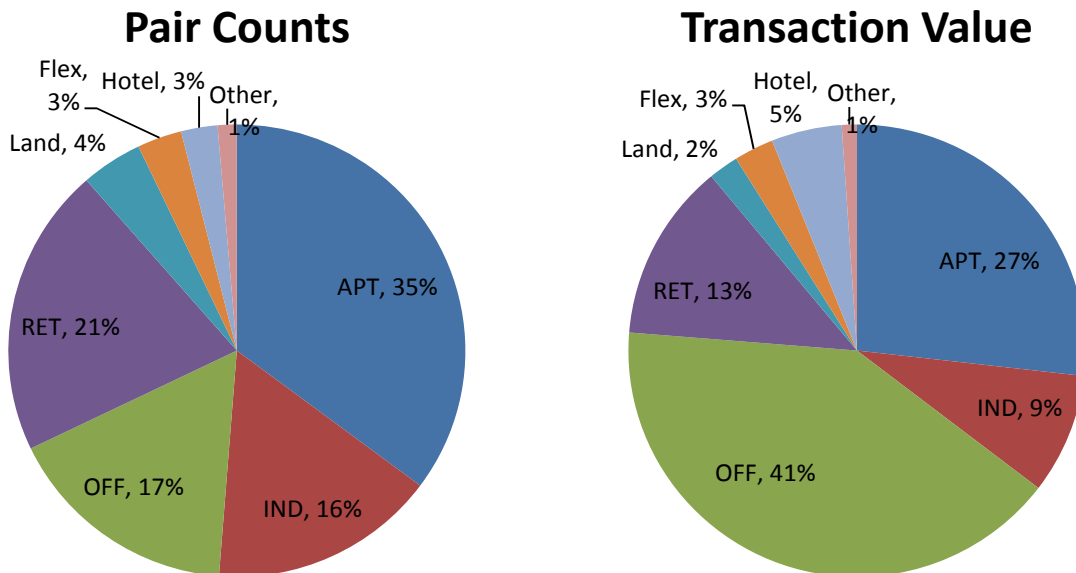
CHART 2

Pair Distribution by Average Annual Price Change



After the filtering process, our final dataset had a total of 85,428 repeat-sale observations covering the period 1996–2010. Chart 3 shows the distribution of repeat-sale pair counts by property type and the corresponding share of transaction value of each property type. Apartment ranks highest in the number of repeat-sale transactions, while office leads in the total value of transactions. This result is expected. Office transactions occur less frequently than apartment sales, but offices tend to sell at higher prices.

CHART 3



The relationship between transaction frequency and transaction value can be further illustrated by the distribution of repeat-sale pair counts over price brackets and the dollar value of transactions in each bracket. As shown in Chart 4, most of the transaction activities are concentrated in the low price bracket below \$1.25 million. As prices increase, the number of transactions diminishes rapidly. Transaction value, on the other hand, is concentrated in the high price brackets. In particular, those transactions greater than \$5 million account for the major share of total transaction value, even though the number of these high-priced transactions represents a small fraction of the total number of transactions.

CHART 4

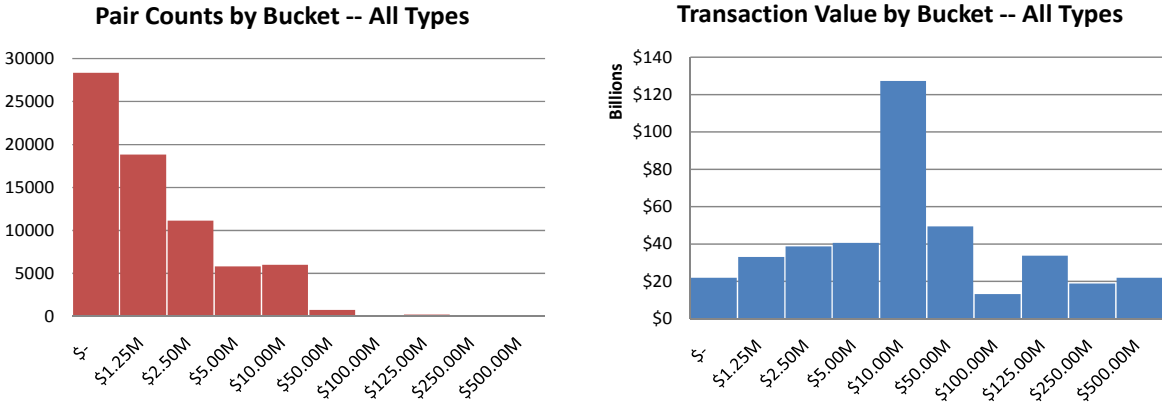
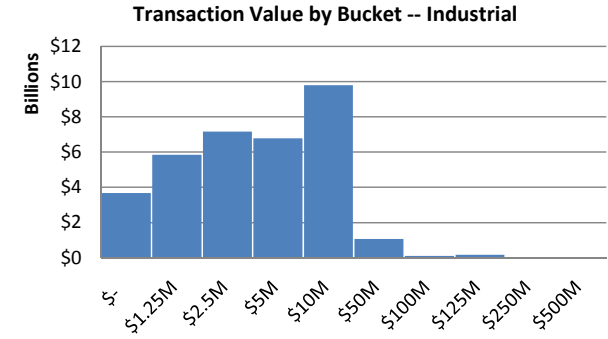
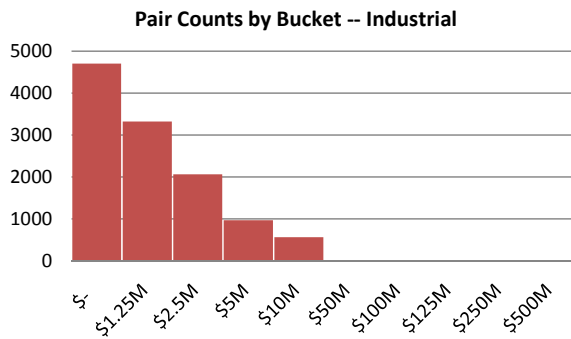
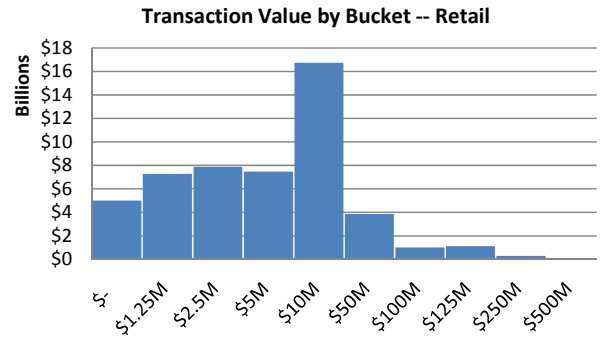
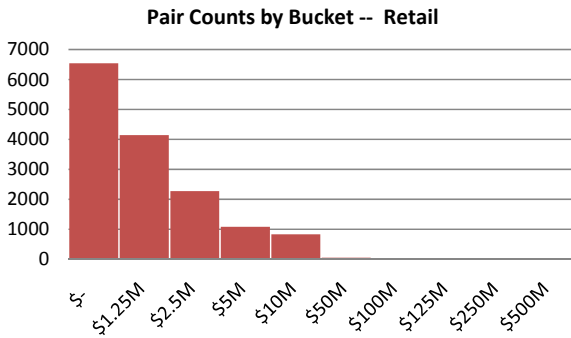
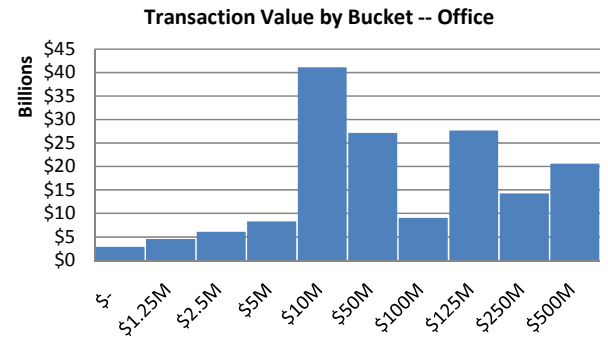
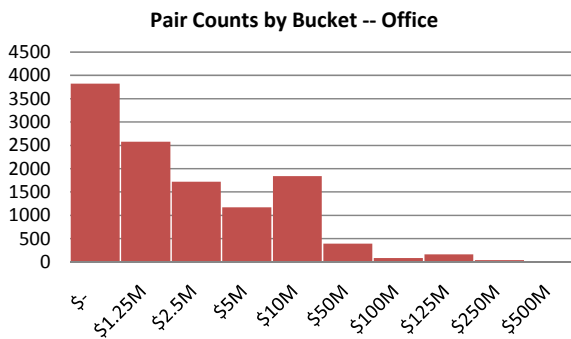
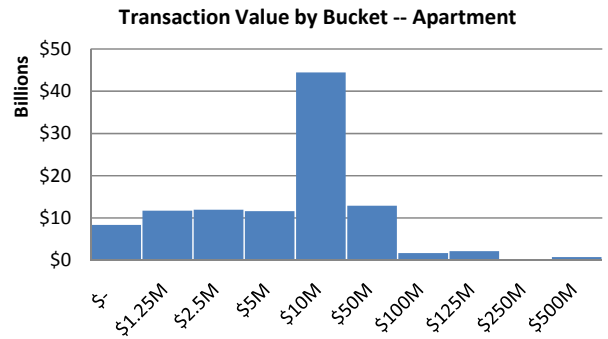
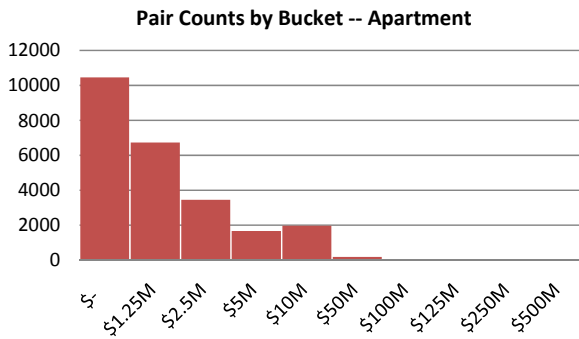


Chart 5 shows the distribution patterns for each of the four major property types. The divergence of transaction frequency and transaction value is significant for apartment. But it is most pronounced for office properties, where the largest number of transactions occur in the brackets below \$10 million, but transactions priced above \$10 million constitute most of the total transaction value. Industrial properties, on the other hand, generally sell within a narrow price range, and as a result, we see transaction activities and value both below \$10 million. We would expect retail to show a divergence similar to that of office. However high-end retail transactions are underrepresented in our repeat-sale dataset due to the fact that retail transactions are generally included in multi-asset portfolio sales. Also the physical characteristics of retail properties change significantly from one sale to the next, which makes retail transactions less likely to meet our criteria for repeat-sale pairs.

CHART 5



Clearly, the heterogeneity of the CRE market is multi-dimensional. There is general divergence between transaction activities and values, and the degree of divergence varies across property types. It is this complexity that differentiates CRE from the housing market and attracts different investors with different investment goals, resulting in widely varying performances. Therefore, our goal is to capture the diversity of CRE market and its unique behavior.

III. METHODOLOGY

Since the repeat-sale regression was first introduced by Bailey, Muth, and Nourse (1963), significant advances have been made by Case-Shiller (1987), Case-Shiller (1989), Shiller (1991), Goetzmann (1992), Clapp-Giacotto (1992), Gatzlaff-Haurin (1997), and others. To date, there are two types of repeat-sale regression methodologies. The first most commonly used method treats every transaction equally, regardless of the value of the transaction. The resulting index is an equal-weighted, geometric mean index. The second method, known as the arithmetic mean repeat-sale regression, introduced by Shiller in 1991, weighs price change by the value of each transaction. The Standard & Poor's Case-Shiller Home Price Index, for example, is an arithmetic mean index. We explored both approaches in developing the CoStar index. See Appendix 1 for a mathematic presentation of the two methodologies.

Generally speaking, the geometric, equal-weighted methodology is more relevant for measuring the performance of individual properties, while the arithmetic, value-weighted index is a better measure of overall market performance. For capturing CRE price movement, however, each method has its pros and cons. Due to the difference between transaction frequency and transaction value, a single, equal-weighted index is inadequate. Because every transaction has the same impact on the results regardless of transaction price, an equal-weighted index will be biased towards low-value deals where transaction frequency is the highest.

The value-weighted index, on the other hand, captures the heavy influence of the high-end properties on overall market value and can be particularly useful for asset allocation analysis. However, the value-weighted index is less relevant for broad investment activities because the majority of transactions occur in the low-value ranges. Also, the value-weighted index may produce statistical noise since a few very expensive sales will have a disproportionate impact on the results. Therefore, in practice, value-weighted methodology has limited applicability, unless there are sufficient data to mitigate the noise.

Table 1 illustrates the differences in the two approaches. All three scenarios under Up Market on the left-hand side have the same appreciation, but the sales prices are different. The equal-weighted results show the same overall price change for all three scenarios, while the value-weighted results are tied closely to the appreciation of higher prices. The same holds true in the Down Market scenarios. The

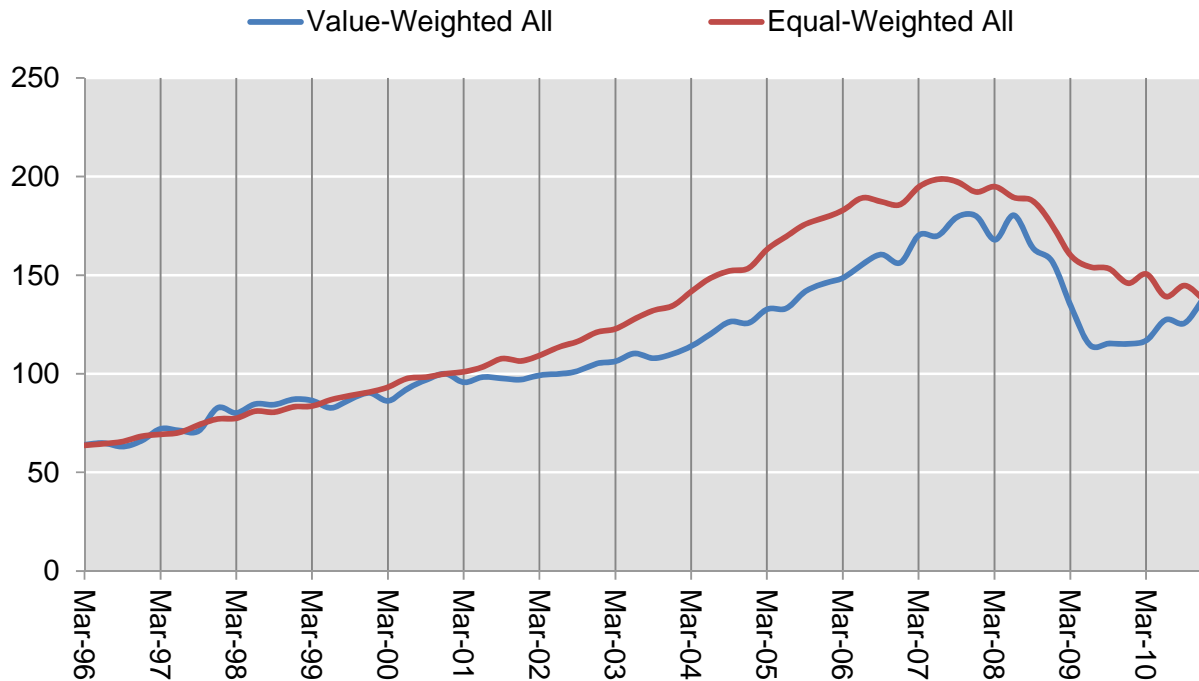
value-weighted method is sensitive to price variations in the high-end and the equal-weighted method focuses only on the rate of appreciation.

TABLE 1

Up Market				Down Market			
Scenario 1				Scenario 1			
	1st Sale Price	Appreciation	2nd Sale Price		1st Sale Price	Appreciation	2nd Sale Price
obs#1	\$ 10,000,000	5%	\$ 10,500,000	obs#1	\$ 10,000,000	-5%	\$ 9,500,000
obs#2	\$ 10,000,000	10%	\$ 11,000,000	obs#2	\$ 10,000,000	-10%	\$ 9,000,000
	Equal-Weighted =	7.47%			Equal-Weighted =	-7.53%	
	Value-Weighted =	7.50%			Value-Weighted =	-7.50%	
Scenario 2				Scenario 2			
	1st Sale Price	Appreciation	2nd Sale Price		1st Sale Price	Appreciation	2nd Sale Price
obs#1	\$ 10,000,000	5%	\$ 10,500,000	obs#1	\$ 10,000,000	-5%	\$ 9,500,000
obs#2	\$100,000,000	10%	\$110,000,000	obs#2	\$100,000,000	-10%	\$ 90,000,000
	Equal-Weighted =	7.47%			Equal-Weighted =	-7.53%	
	Value-Weighted =	9.55%			Value-Weighted =	-9.55%	
Scenario 3				Scenario 3			
	1st Sale Price	Appreciation	2nd Sale Price		1st Sale Price	Appreciation	2nd Sale Price
obs#1	\$100,000,000	5%	\$105,000,000	obs#1	\$100,000,000	-5%	\$ 95,000,000
obs#2	\$ 10,000,000	10%	\$ 11,000,000	obs#2	\$ 10,000,000	-10%	\$ 9,000,000
	Equal-Weighted =	7.47%			Equal-Weighted =	-7.53%	
	Value-Weighted =	5.45%			Value-Weighted =	-5.45%	

Chart 6 presents our national all composite index using the two different methods. As shown, the two indices depict two very different paths of price movement. While both show steady price appreciation from 1996 to 2007, the appreciation rate is lower when the index is value-weighted. Also, the subsequent price fall is much more severe with the value-weighted index. The divergence of the two indices becomes most significant in the last two years. While the value-weighted index shows an obvious price recovery since 2010, the equal-weighted index continues to show price decline. Evidently, each index captures either the high or low side of the market, and neither provides a complete picture by itself. While the two indices together provide complementary information, having two indices depicting the same market in its entirety could be somewhat confusing to the general public. To address this concern, we decided to separate the market into tiers or segments.

CHART 6



However, our efforts to divide transactions into market tiers illuminated some issues in the current practice of segmenting properties by price breakpoints. In the CRE marketplace, \$5 million and \$2.5 million are the traditional cut-off points for determining what is high-end and what is low-end. In the course of our research, we discovered that segmenting market transactions by price breakpoints has great potential to bias the resulting index.

Table 2 presents the results of our simulations demonstrating how price based cut-offs produce bias for the high-end tier. There are four possible ways to divide a market using transaction prices. If the first sale price is the cut-off point, the resulting index will capture falling prices, but not rising prices, resulting in downward bias. Conversely, using the second-sale price as the breakpoint, results in an upward bias. If both first and second sale prices are required to be greater than a certain price breakpoint, then price movements are pushed below the breakpoint into a lower priced market segment, resulting in an understatement of volatility. Using either the first sale or the second sale price as breakpoints, on the other hand, draws in price movements from the market segment below the breakpoints, resulting in an overstatement of volatility.

In summary, the simulation results of four possible cuts show that using the first sale price generates the lowest average annual growth, 2.9%, whereas using the second sales price results in the highest annual growth rate, 7.7%. While the either / or approach generates the highest volatility, 12.2%, using both sales prices results in the lowest volatility, 9.6%.

TABLE 2

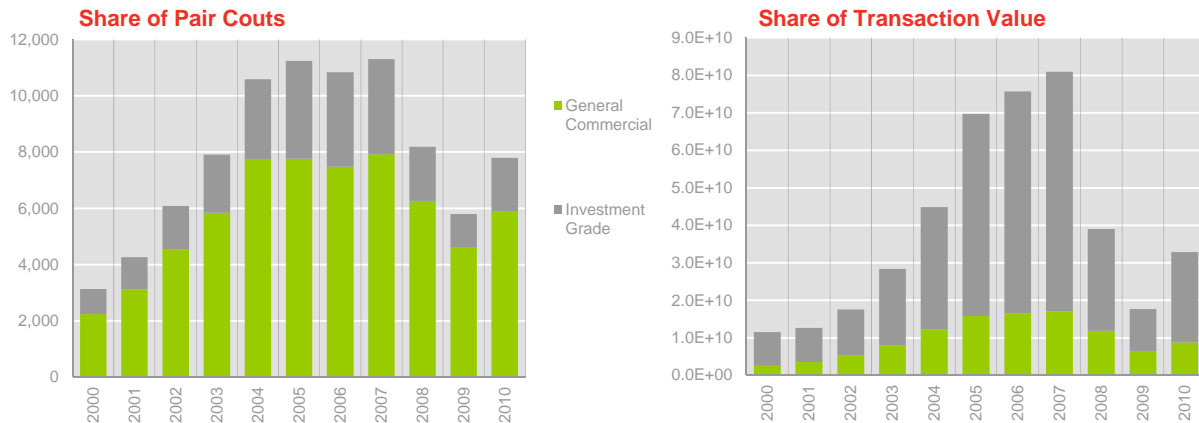
Possible Ways to Extract the High-Value Segment Based on Price	
First Sale Price > 2.5 Million Downward Bias Peak to Trough: 45% Average Annual Growth: 2.9% Volatility: 11.6%	Second Sale Price > 2.5 Million Upward Bias Peak to Trough: 31% Average Annual Growth: 7.7% Volatility: 9.8%
Both First Sale Price and Second Sale Price > 2.5 Million Under State Volatility Peak to Trough: 34% Average Annual Growth: 4.6% Volatility: 9.6%	Either First Sale Price or Second Sale Price > 2.5 Million Over State Volatility Peak to Trough: 43% Average Annual Growth: 6.0% Volatility: 12.2%

The varying results from using price cut-offs to define market segments highlights the flaws in this approach. Because property price is used twice, first to define the data set and then to produce the index, a circular reference is created, and the resulting bias becomes difficult to correct. Given this finding, we decided to try a different approach to differentiate market segments. Rather than use pricing breakpoints, we divided the market into two segments —investment grade and general commercial — based on building characteristics such as square footage and building class. In this paper, the investment grade segment contains the following properties: Class A and B offices with 20,000 square feet or more, industrial and flex properties with 40,000 square feet or more, multifamily properties with 50 units or more, hotels with 150 units or more, and finally retail properties with 20,000 square feet or more. All the remaining properties are designated as general commercial. Using physical characteristics guarantees a consistent set of properties for index development.

The investment grade properties comprise a little less than 30% of the total transactions but capture more than 75% of the transaction value. The general commercial properties tend to be smaller in dollar value but count for a majority of transactions. Chart 7 shows the pair count share and the value share of

the two segments over time. The composition of property types for investment grade is similar to the overall dataset shown in Chart 3. Multifamily still leads in the number of repeat-sale transactions, while office leads in the total value of transactions.

CHART 7



IV. RESULTS & DISCUSSION

Chart 8 presents two equal-weighted indices, one for investment grade properties and the other for general commercial. As shown, the equal-weighted index for investment grade closely resembles the value-weighted index for the entire market. The equal-weighted general commercial index, on the other hand, is very similar to the equal-weighted index for all properties.

Both chart 6 and chart 8 convey the same message — high-value properties underperformed low-value properties for much of the time since 1996. After the downturn in 2009, however, high-value properties have been outperforming their counterparts. The results demonstrated so far illustrate two methodologies, and both capture the market more completely than a single index. We can either use two indexing methods (equal-weighted and value-weighted) to track one overall market, or we can use the same indexing method (the equal-weighted) to track two mutually exclusive market segments. We found the latter approach gives a clearer picture of the market, is less complicated, and is the most consistent.

CHART 8

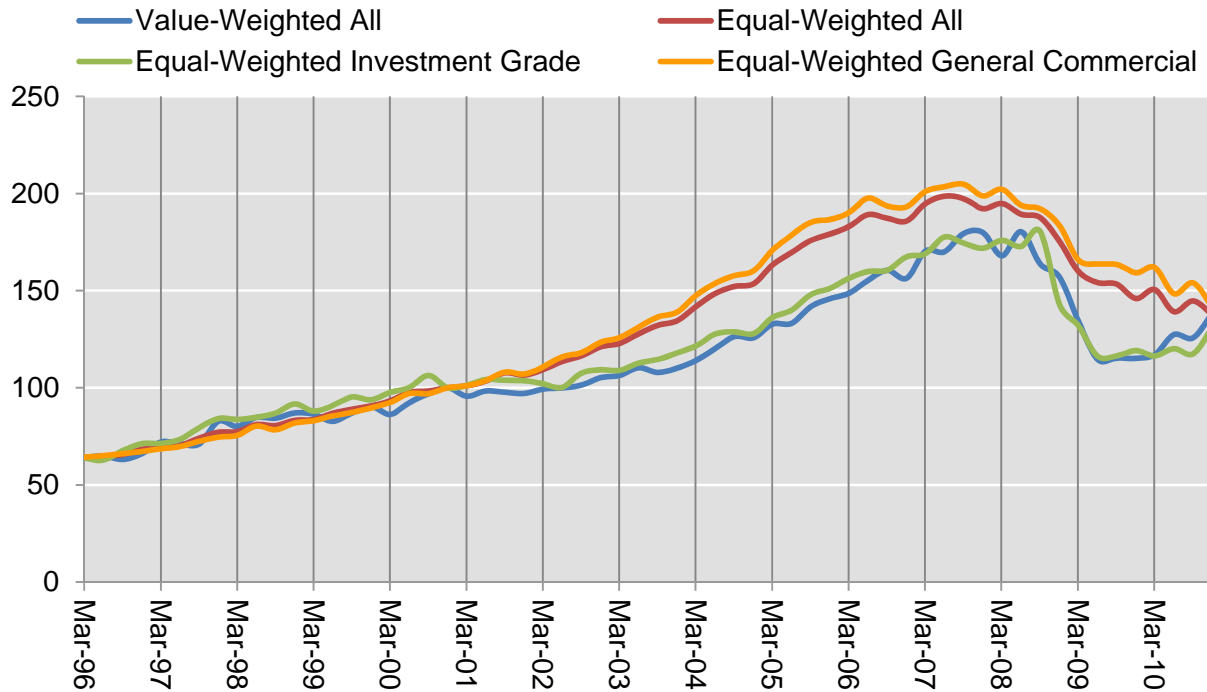


Chart 9 compares the performance of investment grade properties with general commercial for four major property types. Consistent with distribution patterns of transaction frequency and value as seen in Chart 5, office and apartment show the most significant price difference between investment grade and general commercial. Industrial, on the other hand, has the least differentiation between investment grade and general commercial.

While in-depth analysis of market performance is beyond the scope of this paper, there are a couple of observations worth mentioning. In general, the prices of investment grade properties went up and down more dramatically than those of general commercial properties over the period we tracked, and this high volatility of high-value properties has some fundamental implications for CRE investors. Interestingly, this observation differs from the stock market, where small-cap stocks are more volatile. The volatility of high-value property can certainly be explained by structural reasons, such as long construction cycles and long lease terms. However, what also makes commercial real estate assets fundamentally different from stocks is the way real estate is traded, which makes liquidity a significant issue. Most properties trade in lump sums in private search markets, and properties with higher values have fewer potential buyers, making high-value properties less liquid. Conversely, in the stock market, large-cap stocks are more liquid, and thus less volatile, due to a greater number of investors willing to trade fractional ownership shares in any given day. Following this logic, the small-deal CRE market, with its greater number of participants, is more liquid and thus less volatile.

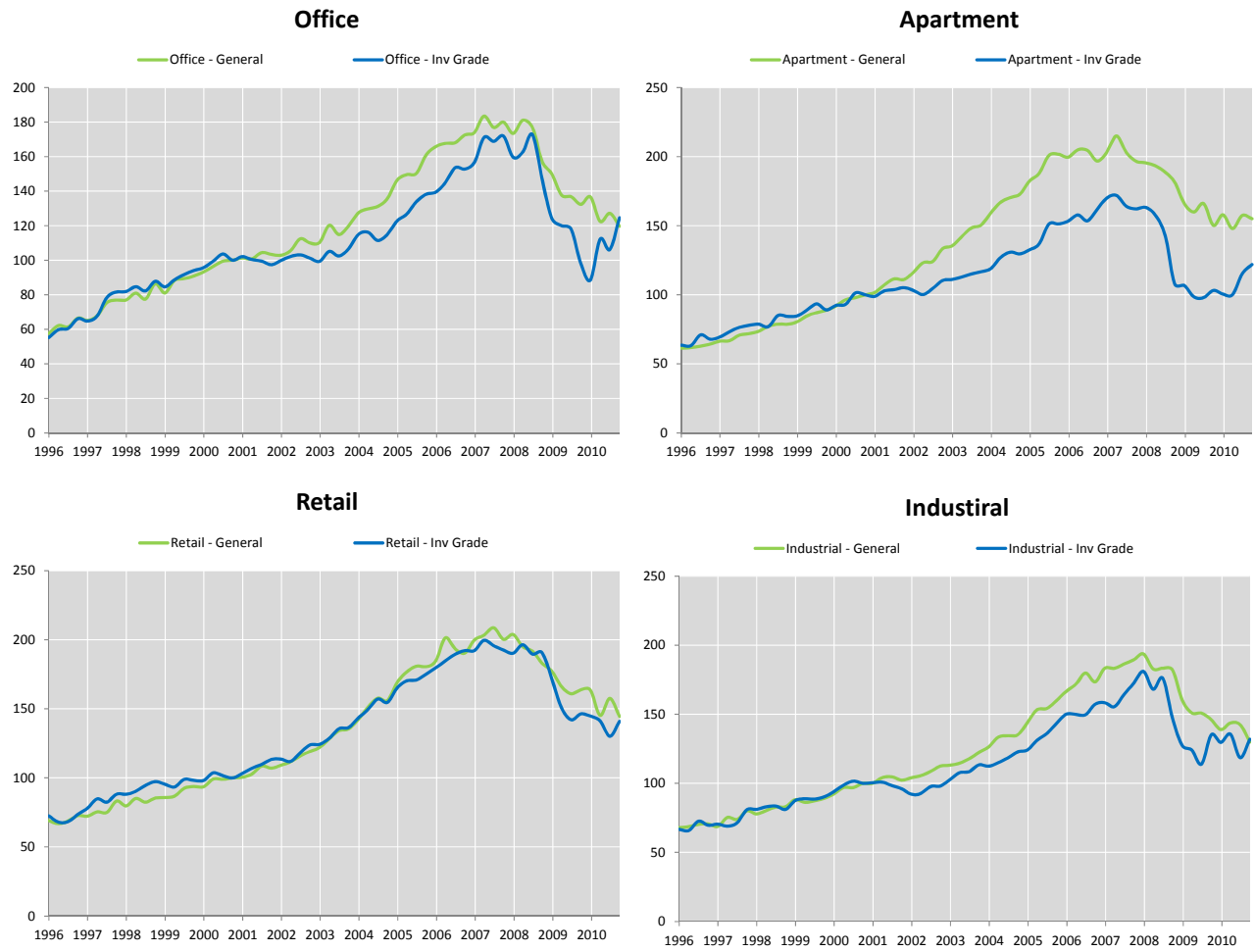
In an efficient market, high volatility must be compensated by high returns. According to our indices, however, the appreciation of investment grade properties was lower than that of general commercial properties most of the time, except in the most recent months. Because return on real estate investment includes both appreciation and income return, which are not included in this study, we cannot conclude definitively whether or not high-value properties have generated returns sufficient to compensate for their higher risk of illiquidity. The issue remains a challenge for CRE investors, particularly for institutional investors.

From the end of 2009, investment grade prices have clearly stabilized and recovered from the bottom. Examining the sub-indices by property type and by tier (Chart 9), we can see that the recent price uptick is caused mainly by the investment grade office and apartment property types. This confirms conventional thinking that high-end properties — the targets for bargain hunting — are the first to recover after a recession. By tracking all levels of performance, however, we show that the recovery is limited to small number of properties, and any generalization based on the performance of a small segment of the market can be misleading. In fact, whether or not the high-end recovery is sustainable depends on a fundamental improvement in the broader market — an improvement that would be indicated by an upward movement of the general commercial index, a market segment that is highly reflective of broad investment activities, but is often ignored in existing real estate research.

V. **SUMMARY**

In conclusion, no single index can fully capture the multifaceted and diverse nature of CRE. However, CoStar's rich dataset made it possible for us to approach the challenge from multiple angles. By comparing value-weighted and equal-weighted indices, we found that using an equal-weighted index to track separate market segments is a more consistent approach, and the result is easy to comprehend. Also, our analysis reveals the conventional approach for using price cut-offs to differentiate market tiers will cause problematic bias in the index. A consistent set of properties defined by physical characteristics is necessary for developing an index that provides accurate benchmarks for various levels of CRE investment activities.

CHART 9



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APPENDIX

A. Geometric Repeat-Sale Regression

With geometric repeat-sale regression (GRS), the logarithm of cumulative price appreciation for a property between two sales is expressed as:

$$Y = \ln\left(\frac{P(t_s)}{P(t_f)}\right) = \sum_t \ln[1 + R(t)]X(t) = \sum_t \beta(t)X(t) \quad (1)$$

$$X(t) = \begin{cases} 1 & t_f < t \leq t_s \\ 0 & otherwise \end{cases}$$

where $P(t_f)$ is the 1st sale price, $P(t_s)$ is the 2nd sale price, $R(t)$ is the appreciation rate at period t , $X(t)$ is a dummy variable, and $\beta(t)$ is the regression coefficient. Because the appreciation rate R is calculated based on the ratio of 1st and 2nd sale prices, all transactions are equally weighted independent of the values of the transactions. With estimated appreciation rate R , the price index is

$$Index(t) = \prod_{t=0}^t [1 + R(t)]$$

In matrix format, the representation of Equation (1) can be expressed as:

$$Y = X \cdot \beta + \varepsilon \quad (2)$$

Assuming the error term follows the Gaussian diffusion process, β can be estimated by the ordinary least square (OLS):

$$\beta_{OLS} = (X'X)^{-1} X'Y \quad (3)$$

For repeated sales occurring between long time durations, the appreciation rate $R(t)$ estimated from Equations (1) and (3) is the average over the period. This average may not capture the appreciation rate at a particular given time. To correct for the heteroskedasticity problem (the longer the time span between two transactions, the more idiosyncratic the errors), a second regression is estimated to find the variance dependence on the time span between two sales:

$$V = \langle \varepsilon^2 \rangle = A + B \times t + C \times t^2 \quad (4)$$

With the expected variance for each pair, a third OLS regression is estimated to obtain interval-weighted coefficients:

$$\frac{Y}{\sqrt{V}} = \sum \frac{\beta(t)X(t)}{\sqrt{V}} \quad (5)$$

Equations (2), (4), and (5) complete the interval-weighted geometric repeat-sale regression (I-GRS).²

B. Arithmetic Repeat-Sale Regression

Arithmetic repeat-sale regression (ARS) is analogous to GRS, but with some modified assumptions. A primary objective of ARS is to provide a value-weighted repeat-sale price index similar to market-cap weighted stock indices.

Following Shiller (1991), we define:

$$\beta_t = \frac{P_0}{P_t}. \quad (7)$$

Here β_t is the inverse of accumulated price appreciation between time t and a base period ($t = 0$). For the base period, $\beta_0 \equiv 1$. The price index is given by

$$Index(t) = \frac{1}{\beta_t}.$$

The price difference of two repeat-sales, after adjusting by the inverse index value β , should be zero with a random distribution error ε ,

$$\beta_k P_{nf} - \beta_t P_{ns} = \varepsilon_n \quad (8)$$

where n denotes property n , and f, s denote time periods of the repeat-sales. To estimate β , we define a dummy variable

$$\Omega_{nt} = \begin{cases} -1 & \text{for first repeat sale of property } n \text{ in time period } t \\ 1 & \text{for second repeat sale of property } n \text{ in time period } t \\ 0 & \text{otherwise} \end{cases}$$

and a matrix Z with elements $Z_{nt} = \Omega_{nt}$ ($t=1, 2, \dots$). Equation (8) can be expressed as

$$Y = X \cdot \beta + \varepsilon$$

² The ordinary least square estimator β_{ols} , Equation (3), can be unreliable when observations are limited. Goetzmann (1992) first suggested the ridge estimator as an additional step to repeat-sale regression if collinearity is present in its parameter matrix due to data limitation. See CCSRI Methodology at http://www.costar.com/uploadedFiles/About_Costar/CCRSI/articles/pdfs/CCRSI-Methodology.pdf for the application of ridge estimator.

where the elements of matrix X and Y are

$$X_{nt} = P_{nt} \cdot \Omega_{nt} \quad (t=1, 2, \dots),$$
$$Y_{nt} = P_{nt} \cdot \Omega_{nt} \quad (t=0).$$

The ARS method calculates the value of β from

$$\hat{\beta} = (Z' \cdot X)^{-1} Z' \cdot Y \quad (9)$$

The resulting $\hat{\beta}$ is an arithmetic value-weighted average of the inverse of price appreciation. For repeated sales occurring between long time durations, the appreciation rate estimated from Equations (7)-(9) is again the average over the period. Interval adjustment for ARS is similar to that of GRS as given in Equations (4) and (5).³

³ ARS often requires a robust weighting procedure to mitigate influence of sale pairs with extreme price change. See CCSRI Methodology at http://www.costar.com/uploadedFiles/About_Costar/CCRSI/articles/pdfs/CCRSI-Methodology.pdf more details.