A Quarterly Transactions-Based Index (TBI) of Institutional Real Estate Investment Performance and Movements in Supply and Demand

by

Jeff Fisher*, David Geltner**, & Henry Pollakowski***
MIT Center for Real Estate
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Abstract

This article presents a methodology for producing a quarterly transactions-based index (TBI) of property-level investment performance for U.S. institutional real estate. Indices are presented for investment periodic total returns and capital appreciation (or price-changes) for the major property types included in the NCREIF Property Index. These indices are based on transaction prices to avoid appraisal-based sources of index "smoothing" and lagging bias. In addition to producing variable-liquidity indices, this approach employs the Fisher-Gatzlaff-Geltner-Haurin (*REE* 2003) methodology to produce separate indices tracking movements on the demand and supply sides of the investment market, including a "constant-liquidity" (demand side) index. Extensions of Bayesian noise filtering techniques developed by Gatzlaff & Geltner (*REF* 1998) and Geltner & Goetzmann (*JREFE* 2000) are employed to allow development of quarterly frequency, market segment specific indices. The hedonic price model used in the indices is based on an extension of the Clapp & Giacotto (*JASA* 1992) "assessed value method", using a NCREIF-reported recent appraised value of each transacting property as the composite "hedonic" variable, thus allowing time-dummy coefficients to represent the difference each period between the (lagged) appraisals and the transaction prices. The index could also be used to produce a *mass appraisal* of the NCREIF property database each quarter, a byproduct of which would be the ability to provide transactions price based "automated valuation model" estimates of property value for each NCREIF property each quarter. Detailed results are available at http://web.mit.edu/cre/research/credl/tbi.html.

Methodology update, May 2009:

The following changes in methodology and production procedures will be made for the TBI as of 1Q09:

- Published indexes will be frozen as of the end of each calendar year. This is for the convenience of users, and reflects experience indicating that backward-adjustments have been minimal and not of economic significance.
- Published indexes will be based on a starting value of 100 as of the inception date of each index (1984Q1 for all-property, 1994Q1 for the sectoral indexes).
- The ridge regression noise filter will be eliminated going forward starting 1Q09 for the all-property index only. Experience indicates that in the all-property index the noise filter has little impact and is not needed subsequent to the early history of the index (where effectively the filter is retained by the freezing of the prior history). Eliminating the noise filter will enable the all-property index to be more independent of the NPI during the preliminary quarterly reports.
- Going forward starting in 1Q09 the "representative property" used to compute the index based on the hedonic price model will have its "hedonic value" (based on the self-reported NPI valuations) re-set to be lagged 2 quarters prior to the current NPI

appreciation level. Experience indicates that NCREIF self-reported valuations are now less lagged than they used to be, suggesting that this change is warranted based on the specification of the quarterly hedonic price model.

- Each index will be published no matter how few are the current transactions observations unless in the judgment of the MIT/CRE TBI manager (presently David Geltner) there is both extremely few current observations ***and*** a spurious or implausible-seeming estimated return. If an index must be skipped due to lack of observations the circumstances will be described in the published quarterly commentary and the index will be back-filled by "straight-lining" as soon as data is next available. (This is the procedure followed for the retail index for 4Q2008-1Q2009.)

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> *"In summary, we argue that the NCREIF Index is ready to evolve into two more specialized successor families of index products: one tailored for fundamental asset class research support, and the other tailored for investment performance evaluation benchmarking and performance attribution."*
> -- From: D.Geltner & D.Ling, Benchmarks & Index Needs in the U.S. Private Real Estate Investment Industry: Trying to Close the Gap (A RERI Study for the Pension Real Estate Association), October 17, 2000.

This article addresses the need for a "fundamental asset class research" index of real estate investment performance and market conditions by presenting a state-of-the-art transactions-based index (TBI) of commercial real estate. The TBI does not replace the appraisal-based NCREIF Property Index (NPI), but complements it.[1] It applies modern econometrics to distill information from property transaction prices and results in an index that provides the academic and industry investment research communities with certain useful characteristics that the appraisal-based NPI lacks.[2]

Since the advent of modern portfolio theory and rigorous investment management and analysis almost 50 years ago, asset classes in the core of the institutional investment portfolio have required indices of total returns that accurately track investment performance

[1] See Geltner & Ling (2001, 2005).
[2] As of 2006, this index is being produced by the Commercial Real Estate Data Laboratory at the MIT Center for Real Estate. The TBI is updated quarterly within 45 days of the end of each quarter, and is available to the public. See http://web.mit.edu/cre/research/credl/tbi.html.

and which reflect the state of the market for the asset class. The NPI was developed over a quarter century ago to address this need for real estate.

While the NPI is quite useful, and appropriate for many functions (e.g., as a benchmark for investment manager performance), the research community has never been entirely satisfied with it . The NPI is based on appraised values of the properties in the index. Given the nature of the appraisal process, and because most properties in the index are not fully or independently reappraised every quarter, the index exhibits a degree of “smoothing” and “lagging” relative to the underlying real estate market.[3] This can be problematic for some research and analysis purposes, such as some types of multi-asset class studies and comparisons (including portfolio optimization), and studies of market turning points or historical market conditions. Although techniques have been developed to “unsmooth” or “reverse-engineer” the NPI to eliminate the smoothing and lagging, these techniques are inevitably somewhat ad hoc or mathematically complex, and difficult for the broader investment community to understand.[4]

Thus studies of the fundamental nature and characteristics of the real estate asset market would greatly benefit from an accurate and transparent transactions-based index that avoids the smoothing and lagging in the NPI. As the NCREIF Index has matured, its database has grown to include a sufficiently large number of property transactions, meaning that in combination with recent developments in econometric methodology, it is

[3] See for example: Geltner & Miller (2001), Chapter 25; and for a literature review: Geltner, MacGregor & Schwann (2003).
[4] See for example: Brown (1985), Blundell & Ward (1987), Quan & Quigley (1989, 1991); Geltner (1991); Giacotto & Clapp (1992); Geltner(1993); Fisher, Geltner & Webb (1994); Lai & Wang (1998); Fisher & Geltner (2000), Fu (2003).

possible to produce a useful transactions-based index from the NCREIF database. The transaction-based index (TBI) is characterized by the following features:

- It is transactions-based index, calibrated directly on the transaction prices of properties sold each quarter from the NPI database, although it also makes use of all the information available in the appraisal-based officially-reported values of all of the properties in the NPI.

- It is capable of on-going, regular production at the quarterly frequency, reporting total investment return as well as the capital appreciation return component each quarter, at the all-property level and at the level of the four major property sectors: office, industrial, retail, and apartment.

- It could be used for the "mass appraisal" of all properties in the NPI database every quarter, enabling an up-to-date, transactions price based estimate of the value of each property (though such property-level valuation cannot be reported publicly as it would violate NCREIF's masking guidelines).

- It is based on state-of-the-art econometric techniques developed recently in the real estate economics academic community, including correction for possible sample selection bias in the sold properties and noise filtering at the quarterly frequency.

- In addition to a standard transactions price based index that reflects the pro-cyclical variable liquidity in the real estate asset market, the TBI allows separate estimation of movements on the demand side and on the supply side of the institutional property market. The demand side index can be interpreted as a "constant liquidity index" (CLI), which collapses both price and trading volume measures of changes in market conditions into a single metric, the percentage change in price that would allow a constant expected time on the market or constant turnover ratio of trading volume in the market.

The TBI exhibits some of the major characteristics that we would expect from a transactions-based index. It shows evidence of leading the NPI in time based on the timing of the turning points of the major historical cycle in the asset market, and it exhibits greater volatility and less autocorrelation (less inertia), including less seasonality. Furthermore, the additional volatility seems to "make sense", including quarterly down-ticks during notable historical moments when we would expect the property market to have fallen at least temporarily (but when the NPI does not register losses), such as the tax act of 1986 (unfavorable to real estate), the stock market crash of 1987, the Gulf War of 1991, the financial crisis of 1998, the September 2001 terrorist attack, and the start of the Iraq War in 2003.

The remainder of this article is organized as follows. Section 1 presents the basic theory and methodology on which the TBI is based, including its extension to include demand and supply indices. Section 2 describes the data and the specific estimation and index construction techniques used in the index. Section 3 presents the index development results, and some basic analysis of the index returns, including a simple portfolio optimization analysis. A conclusion section summarizes.

1. Theory and Methodology

To facilitate understanding not only of the variable liquidity transactions index but also of the demand and supply indices, we must begin with a fundamental model of the processes underlying the observed transaction prices and the observed volume of transactions each period within the NCREIF population of properties. The model we use was developed by Fisher, Gatzlaff, Geltner, and Haurin (2003), referred to hereafter as FGGH. The indices presented in this paper are based on this model, with some enhancements to the specific estimation methodology, which we will describe here.

The FGGH model represents a double-sided search market with heterogeneous participants and heterogeneous properties. Observable transaction prices and observable transaction volume both derive from interaction between two populations of market participants: potential buyers (non-owners) on the demand side, and potential sellers (owners) on the supply side. The model is depicted graphically in Exhibit 1, with the three panels showing three successive points in time. The horizontal axis depicts reservation prices, and the bell-shaped curves show the frequency distributions of potential buyers' (the left-hand curve) and potential sellers' (the right-hand curve) reservation prices. The dispersion depicted in these reservation price distributions reflects the heterogeneity of individual market participants' perceptions of values of the properties (as well as their differing search costs, etc). The overlap between the distributions allows for profitable trading of properties, as reflected in observed transaction volume. As time passes and news arrives, both the buyer and seller populations revise their reservation prices, but not necessarily in identical ways. The result is that the overlap region varies over time, corresponding to variation in the trading volume (the turnover ratio or "liquidity") within the population of properties. Pro-cyclical variable liquidity, that is, greater transaction volume during “up” markets (which is a striking empirical fact in real estate markets), suggests that the demand side (potential buyers) reservation price distribution moves quicker and/or farther than the supply side (potential sellers) reservation price distribution, in response to the arrival of news relevant to value.

Insert Exhibit 1 about here.

Hedonic modeling controls for heterogeneity across properties, and Heckman’s procedure controls for sample selection bias in the transacted properties by modeling both transaction price and transaction sales propensity. By modeling both price and sale probability it is possible to identify property value (i.e., reservation price) equations separately for both the buyer population and the seller population. The buyers’ valuations provide the demand side valuations and the constant-liquidity index, while the sellers’ valuations provide the supply side index. The specifics of the methodology are presented below, which is an extension of FGGH.

On the demand side of the market is a population of potential buyers whose reservation prices are modeled by equation (1):

$$RP_{it}^{b} = \sum \alpha_{j}^{b} X_{ijt} + \sum \beta_{t}^{b} Z_{t} + \varepsilon_{it}^{b} \tag{1}$$

Similarly, on the supply side of the market is a population of potential sellers (owners) whose reservation prices are modeled by equation (2)

$$RP_{it}^{s} = \sum \alpha_{j}^{s} X_{ijt} + \sum \beta_{t}^{s} Z_{t} + \varepsilon_{it}^{s} \qquad (2)$$

In these equations, the variables are described below:

RP_{it}^{b}, RP_{it}^{s} = the natural logarithm of a buyer's (seller's) reservation price for asset i as of time t (the price at which agents will stop searching or negotiating and agree to an immediate transaction);

ε_{it}^{b}, ε_{it}^{s} = normally distributed mean zero random errors (reflecting heterogeneity within the buyer and seller populations, respectively);

X_{ijt} = a vector of j asset-specific characteristics of the properties relevant to valuation (the *"hedonic"* variables);

Z_{t} = a vector of zero/one time-dummy variables (Z_t =1 in quarter *t*).

In (1) and (2), the $\sum \alpha_{j}^{b} X_{ijt}$ and $\sum \alpha_{j}^{s} X_{ijt}$ components reflect systematic asset-specific values common to *all* potential buyers and all potential sellers, respectively. Temporal variation is possible in the X_{ijt} (hence the *t* in the subscript), reflecting variation over time in the perceived hedonic quality of the property. In typical applications of real estate hedonic value modeling the X_{ijt} vector consists of a number of qualitative and quantitative dimensions of property utility, such as size, age, location, etc. In the case of commercial investment property valuation, many of these hedonic dimensions of utility would be summarized quantitatively in the rent that the property can charge (which, of course, also relates directly to the financial valuation of the asset).

Within the NCREIF database, an even more complete summary of the value of the property is the most recent appraised value of the property. In the spirit of the Clapp & Giacotto (1992) "assessed value method", the most recent appraised value of each property in the database may be used as a summary statistic collapsing the entire X_{ijt} vector into a single scalar value for each property in each time period. We will label this variable A_{it} and note that it clearly reflects both cross-sectional and temporal dispersion. Thus, the $\sum \alpha_j^b X_{ijt}$ and $\sum \alpha_j^s X_{ijt}$ components are simplified to: $\alpha^b A_{it}$ and $\alpha^s A_{it}$.[5]

The dispersion within the buyer reservation price distribution is governed by the dispersion in ε_{it}^b, while the dispersion within the seller distribution is governed by ε_{it}^s. These error terms are random, varying across the individual potential buyers and across individual potential sellers, reflecting unobservable characteristics of the parties and their perceptions of the properties.

In contrast, the β_t^b and β_t^s coefficients represent systematic and common factors across all buyers and all owners (respectively), within each period of time. β_t^b and β_t^s are also common across all assets (*i*) within each period of time (like a time-varying "intercept"), reflecting the population as a whole during period *t*. The combined effect of the differences between the α^b and α^s coefficients (given the current values of A_{it}), and between the β_t^b and β_t^s coefficients is therefore what distinguishes the buyer and seller

[5] Note that since the reservation price model is in log values, we would also take the log of the appraised value.

reservation price distributions systematically from each other, each period. These population-specific responses govern the central tendency within each population, in each period of time.

Movements over time in the valuations' central tendencies are reflected in the changes over time in the $\left(\alpha^{b} A_{it} + \sum \beta_{t}^{b} Z_{t}\right)$ or $\left(\alpha^{s} A_{it} + \sum \beta_{t}^{s} Z_{t}\right)$ components, for the buyers and sellers respectively. Such value changes over time may be due either to changes over time in the values of the A_{it} summary hedonic variables (which reflect both cross-sectional and longitudinal dispersion), or to the periodic variation in the β_{t}^{b} and β_{t}^{s} parameters (which reflect purely longitudinal changes in the "intercepts", or valuation components not otherwise captured in the A_{it} variables). In the present NCREIF application in which we are using each property's recent appraisal (as of record 2 quarters previously) as the catch-all hedonic variable, the β_{t} intercepts will reflect primarily only the difference each period between the central tendency of the appraisals and the central tendency of the transaction prices, for period *t*.

Transactions are consummated when and only when the buyer's reservation price exceeds the seller's: $RP^{b}_{it} \geq RP^{s}_{it}$. Only under this condition do we observe a transaction price, P_{it}. In other words, consistent with rational investment decision-making (NPV maximization):

$$P_{it} = \begin{cases} observed, & \text{if } RP_{it}^{b} - RP_{it}^{s} \geq 0 \\ unobserved, & \text{if } RP_{it}^{b} - RP_{it}^{s} < 0. \end{cases} \tag{3}$$

The observed transaction price must lie in the range between the buyer's and seller's reservation prices, both of which are unobserved. The exact price depends on the outcome of a negotiation, and depends on the strategies and bargaining power of the two parties. To produce demand and supply indices, we follow FGGH and assume that the transaction price will equal the midpoint between the buyer's and seller's reservation prices.[6]

Using (1) through (3) and our midpoint price assumption, we see that among sold assets the expected transaction price (for asset *i* as of time *t*) is:

$$E\left[P_{it}\right] = \frac{1}{2}\left(\alpha_j^b + \alpha_j^s\right)A_{it} + \frac{1}{2}\sum_t \left(\beta_t^b + \beta_t^s\right)Z_t + \frac{1}{2}E\left[\left(\varepsilon_{it}^b + \varepsilon_{it}^s\right)\middle| RP_{it}^b \geq RP_{it}^s\right]. \qquad (4)$$

The expectation of the sale price consists of three components: the expected midpoint between the asset-specific buyer and seller perceptions of value, the midpoint between the market-wide buyer and seller period-specific intercepts, and the expected value of the random error, which is itself the midpoint between the buyer's and seller's random components *among the parties that consummate transactions*. This last term is, in general, nonzero, because of the condition that the buyer's reservation price must exceed the seller's reservation price in any observable consummated transaction.

[6] There is no reason to assume that either side of the negotiation will systematically have greater bargaining power or negotiating ability. Our assumption of trades at the midpoint is more realistic and more general than the assumption used in many previous studies in the real estate literature that all trades are at the buyer's offer price, and the midpoint price assumption is consistent with Wheaton's (1990) model of the housing market as a double-sided search market. However, within the framework developed in this section it is technically straightforward to replace the midpoint assumption with other specific assumptions (for example, allowing variable pricing across the cycle). Analysis available from the authors suggests that alternative assumptions yield results either similar to, or empirically less plausible than, the results obtained from the midpoint price assumption.

We can measure E[P_{it}] by estimating (4) via the following regression based on observed transaction prices within the NCREIF population:

$$P_{it} = a\ A_{it} + \sum_t \beta_t Z_t + (\varepsilon_{it}\ \left| RP_{it}^b \geq RP_{it}^s \right.) \qquad (5)$$

where: $a = \frac{1}{2}\left(\alpha^b + \alpha^s\right)$, $\beta_t = \frac{1}{2}\left(\beta_t^b + \beta_t^s\right)$, and $\varepsilon_{it} = \frac{1}{2}\left(\varepsilon_{it}^b + \varepsilon_{it}^s\right)$ (and recall that Z_t is a zero/one time-dummy). Such a model will predict an estimated value, $\hat{P}_{it}$, for each property *i* in each period *t* within the NCREIF population.

As noted, the stochastic error term in (5) may have a nonzero mean because the observed transaction sample consists only of selected assets, namely, those for which $RP^b_{it} \geq RP^s_{it}$. If $E\left[\left(\varepsilon_{it}^b + \varepsilon_{it}^s\right) \left| RP_{it}^b \geq RP_{it}^s \right.\right] \neq 0$, this will cause simple OLS estimation of (5) to have biased coefficients. As described in FGGH, this sample selection bias problem can be corrected by the well known Heckman procedure which involves estimation of a separate probit model of property sale probability.

In our context, this sales model is useful not only in the Heckman procedure to correct for sample selection bias in the value model, but also to enable separate identification of the buyers (demand side) and sellers (supply side) valuation models, the former of which presents the constant liquidity valuation, as described in FGGH.

The probit model of property sale probability is based fundamentally on the decision of whether to sell an asset or not. The latent variable describing the decision for the i-th asset in period t is S_{it}^{*}:

$$S_{it}^{*} = RP_{it}^{b} - RP_{it}^{s} . \tag{6}$$

S_{it}^{*} is not observable, only the outcome S_{it} is observed:

$$S_{it} = \begin{cases} 1, & if \;\; S_{it}^{*} \geq 0 \\ 0, & \text{if otherwise.} \end{cases} \tag{7}$$

In other words, a sale occurs if and only if $RP^{b}_{it} \geq RP^{s}_{it}$, in which case S_{it} = 1, otherwise S_{it} = 0.

Equation (6) defines S_{it}^{*} to equal the difference between the buyer's and seller's reservation prices for the asset. Subtracting (2) from (1) as in (6) yields:

$$S_{it}^{*} = (\alpha^{b} - \alpha^{s}) A_{it} + \sum (\beta_{t}^{b} - \beta_{t}^{s}) Z_{t} + (\varepsilon_{it}^{b} - \varepsilon_{it}^{s}) . \tag{8}$$

Following FGGH, define: $\omega = \alpha^{b} - \alpha^{s}$, $\gamma_{t} = \beta_{t}^{b} - \beta_{t}^{s}$, and $\eta_{it} = \varepsilon_{it}^{b} - \varepsilon_{it}^{s}$. The Z_t variable here is the same as that in (1), (2), and (5), a zero/one time-dummy variable. Equations (7) and (8) can be estimated as a probit model:

$$\Pr[S_{it} = 1] = \Phi[\omega \; A_{it} + \sum \gamma_{t} Z_{t}] \tag{9}$$

where $\Phi[\ ]$ is the cumulative density function (cdf) of the normal probability distribution evaluated at the value inside the brackets, based on A_{it} and Z_t. The probit model estimates the coefficients and residuals only up to a scale factor. The estimated coefficients in (9) are ω/σ and γ_t/σ, and the estimated error is η_{it}/σ, where $\sigma^2 = Var(\varepsilon_{it}^b - \varepsilon_{it}^s)$. Label the estimated probit coefficients $\hat{\omega}_t$ and $\hat{\gamma}_t$, so that: $\hat{\omega} = \omega/\hat{\sigma} = (\hat{\alpha}^b - \hat{\alpha}^s)/\hat{\sigma}$, and $\hat{\gamma}_t = \gamma_t/\hat{\sigma} = (\hat{\beta}_t^b - \hat{\beta}_t^s)/\hat{\sigma}$.

This allows unbiased and consistent estimation of the price model, which is thus modified from (5) to include the inverse Mills ratio, λ_{it}, as indicated in equation (10) below.[7]

$$P_{it} = a\ A_{it} + \sum \beta_t Z_t + \sigma_{\varepsilon\eta}\lambda_{it} + \upsilon_{it}. \qquad (10)$$

As equation (10) is estimated based on a sample of transaction prices, this model allows the construction of a transaction-based index of the NCREIF population of properties. This can be done in at least two ways, both of which begin with the price model's predicted value of each property, each period:

$$\hat{P}_{it} = \hat{a}A_{it} + \sum \hat{\beta}_t Z_t + \hat{\sigma}_{\varepsilon\eta}\lambda_{it} \qquad (11)$$

The TBI that we have constructed is based on a "representative property" *p*. Property *p* is characterized by a typical or average value of A_{it} and of λ_{it} each period, and also by a typical income flow (call it CF_{pt}). Then, the index returns are based on the predicted

[7] As described in the FGGH (2003) appendix, $\hat{\sigma}$ is a standard output of econometric software packages that implement the Heckman procedure. Such packages also correct for heteroskedasticity in the procedure.

value of property *p* each period and property *p*'s cash flow each period. Thus, in period *t* the capital return for Property *p* (and by construction, for the index as well) is:[8]

$$g_{pt} = \left(\exp[\hat{P}_{pt}] - \exp[\hat{P}_{pt-1}]\right) / \exp[\hat{P}_{pt-1}] \tag{12a}$$

and the income return is:

$$y_{pt} = \left(CF_{pt}\right) / \exp[\hat{P}_{pt-1}] \tag{12b}$$

and the total return is:

$$r_{pt} = g_{pt} + y_{pt} \tag{13}$$

A second way to construct an index is "mass appraisal". In this approach equation (11) is used to produce an estimated value of each property in the NPI database, each period: $\hat{P}_{it}$. The total return and capital return is then computed for each property, each period, in the same manner as above for the representative property:

$$r_{it} = \frac{CF_{it} + \exp[\hat{P}_{it}] - \exp[\hat{P}_{it-1}]}{\exp[\hat{P}_{it-1}]} = \frac{CF_{it}}{\exp[\hat{P}_{it-1}]} + \frac{\exp[\hat{P}_{it}] - \exp[\hat{P}_{it-1}]}{\exp[\hat{P}_{it-1}]} = y_{it} + g_{it} \tag{14}$$

Then these individual property returns are aggregated across all properties in the NPI each period. The aggregation may be by equal-weighting across the properties, or value-weighting (as in the official NPI). In the case of the latter the index return is computed as:

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[8] Recall that $\hat{P}_{pt}$ is in log levels. Exponentiation is required to convert from log levels to straight levels to define a simple periodic geometric return index instead of a continuously-compounded return index.

$$r_t = \sum_i \left[\left(\frac{\exp[\hat{P}_{it-1}]}{\sum_i \exp[\hat{P}_{it-1}]} \right) r_{it} \right] \tag{15a}$$

In the former case (equal weighting), it is simply:

$$r_t = \sum_{i=1}^{N_t} \frac{r_{it}}{N_t} \tag{15b}$$

where N_t is the total number of properties in the NPI in period t.

Because the underlying hedonic value model (10) is a log value model, the above-described mass appraisal procedure will result in a slight bias in the estimated straight level values obtained from exponentiating the predicted log values of (11), and this bias will induce a slight error (but no bias) in the return index.[9] These effects are very minor and may be corrected through well known mathematical adjustments (Neyman and Scott, 1960; Goldberger, 1968; Miller, 1983).

Note that the estimation of each individual property's value as of each period via equation (11) not only enables the construction of a mass appraisal index, but also allows provision of the transactions-based estimated value of each property each period, a value that might be of interest to the property owners.

The above described procedures, based on the price model in equation (10), provide transactions-based versions of the NCREIF Index. As noted above, we use the representative property approach in our TBI. As the hedonic variable is represented by

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[9] The mathematical rule known as "Jensen's Inequality", combined with the concavity of the log function, causes the average of the logs to always be ***<u>less than</u>*** the log of the average. This results in a slight downward bias in the estimated log value level $\hat{P}_{it}$ in equation (11).

the current appraised value of each property each period, A_{it} , it is easy to see how this model incorporates all of the information available in the appraisals, and adds to that any additional information conveyed by the current transaction prices of properties sold from the NPI during period *t*. The estimated value of each property is simply its appraised value (lagged 2 quarters) plus the coefficient on the time dummy variable corresponding to the current quarter *t*. The time-dummy coefficient reflects the difference between the value indication implied by current transactions minus that implied by the appraisal. To the extent that transaction prices are more current than these appraised values, the value model will capture that difference.[10]

It is important to note that the result up to here provides what can accurately be described as a *variable liquidity* index. That is, while the index accurately represents typical transaction prices prevailing among consummated deals in the market each quarter, such prices reflect varying ease or ability to sell properties across time. In other words, the index reflects varying transaction volume or turnover, and hence, varying “liquidity” over time (as thusly defined). This is because liquidity, as indicated by trading volume or transaction frequency, varies over time in the commercial real estate investment market. Furthermore, this variation is systematic and pro-cyclical, with greater liquidity during “up” markets, and less during “down” markets.[11] Elaborating from FGGH, the above-described variable-liquidity valuation and returns estimates can

[10] It should be noted that when estimated on a pooled database this model specification cannot avoid a potential danger of collinearity between the appraised value variable and some of the time-dummy variables. Such collinearity could cause an under-estimation of some of the time-dummy coefficients, which could cause the resulting index to understate the difference between the transaction price based valuations and the appraisal-based NPI valuations. This point will be discussed further later in this paper.

[11] One cause of such variable liquidity in the NPI could be a type of “self-fulfilling prophecy” of transactions occurring at or near appraised values, first suggested by Fisher, Geltner, & Webb (1994). If NCREIF members are under pressure not to sell properties at prices below appraised value, and if appraised values lag behind market values, then it will be difficult to sell properties during down markets.

be adjusted to reflect constant liquidity over time (that is, constant “ease of selling”, or constant expected time-on-the-market). As described below, this procedure also allows the separate identification of indices of demand side and supply side valuations and market movements over time. Indeed, the index of movements on the demand side of the market is the “constant liquidity” index.[12]

We begin by recalling that equation (10) provides a model of observed equilibrium transaction prices in the relevant property market while equation (9) provides a model of observed equilibrium transaction volume in that market as reflected in the sale probability of a given asset. Each of these equations reflects the movements in the demand and supply sides of the property market, but in different ways. This enables these two models to be treated simultaneously to identify explicit demand and supply side indices for the market, as follows.

First consider the demand side of the market. Based on equation (1), the central tendency of the buyers’ valuations is given by

$$V_{it}^{b} = \sum \alpha_{j}^{b} X_{ijt}^{P} + \beta_{t}^{b} = \alpha^{b} A_{it} + \beta_{t}^{b} \tag{16}$$

[12] One reason why some real estate investors and academics have expressed interest in the demand-side (or “constant liquidity”) index is the concern about real estate liquidity, and how this liquidity tends to vary considerably and “pro-cyclically”, that is, when the market is down liquidity “dries up”. This renders somewhat questionable the direct comparison of transaction prices between when the market is “up” and when it is “down”, the sort of comparison that is implied by return indexes that do not control for variable liquidity. Suppose average prices are 30% lower in the trough than in the peak, based on the deals that get consummated. But is 30% really the complete measure of the difference in the market values between those two points in time (and in the cycle)? You couldn’t sell nearly as many properties nearly as quickly or easily at the 30% lower prices in the trough as you could at the peak. Controlling for this difference in liquidity between peak and trough, the fall in market value might be more like 40%, for example. This is one way to interpret and use the constant liquidity index.

and changes in demand are determined by movements in the buyers' reservation price distribution. In log differences, these changes (capital returns) are given by:[13]

$$V_{it}^{b} - V_{it-1}^{b} = \alpha^{b}\left(A_{it} - A_{it-1}\right) + \beta_{t}^{b} - \beta_{t-1}^{b} \tag{17}$$

Estimates of the buyers' coefficients, α^{b} and β_{t}^{b} can be derived as follows. First, estimation of (10) yields $\hat{a}_{j}$ and $\hat{\beta}_{t}$, and from (4) we see that:

$$\begin{aligned} \hat{a} &= (1/2)\left(\hat{\alpha}^{b} + \hat{\alpha}^{s}\right) \\ \Rightarrow \hat{\alpha}^{b} &= 2\hat{a} - \hat{\alpha}^{s} \end{aligned}$$

and: (18)

$$\begin{aligned} \hat{\beta}_{t} &= (1/2)\left(\hat{\beta}_{t}^{b} + \hat{\beta}_{t}^{s}\right) \\ \Rightarrow \hat{\beta}_{t}^{b} &= 2\hat{\beta}_{t} - \hat{\beta}_{t}^{s} \end{aligned}$$

From the probit estimation (9) and its underlying equation (8) we have:

$$\hat{\omega} = (\hat{\alpha}^{b} - \hat{\alpha}^{s})/\hat{\sigma}$$

and: (19)

$$\hat{\gamma}_{t} = (\hat{\beta}_{t}^{b} - \hat{\beta}_{t}^{s})/\hat{\sigma}$$

Thus, we can solve (18) and (19) simultaneously to obtain[14]:

[13] Recall that Z_t is a zero/one time-dummy variable, so the change in the market value between period *t-1* and period *t* simply equals the difference between the two time-dummy coefficients.

[14] Note that $\hat{\sigma}$ equals two times the "probit sigma" parameter that is automatically output standard software in probit estimation routines. (See FGGH Appendix.) Thus, the adjustments in equation (20) simply equal the probit sigma times the probit coefficient estimates.

$$\hat{\alpha}^b = \hat{a} + \tfrac{1}{2}\hat{\sigma}\hat{\omega} \ .$$

And: (20)

$$\hat{\beta}_t^b = \hat{\beta}_t + \tfrac{1}{2}\hat{\sigma}\hat{\gamma}_t$$

Thus, an estimate of the buyers' valuation each period can be obtained from (20) and (16):

$$\hat{V}_{it}^b = \hat{\alpha}^b A_{it} + \hat{\beta}_t^b \qquad (21)$$

As described in FGGH, such an estimate of buyers' valuations can be interpreted as a *constant liquidity* (that is, constant ease of selling, or constant expected time-on-the-market) value estimate for property i . The demand side valuation estimate in (21) can be used to produce a constant-liquidity transaction-based index of capital value changes or of total returns, using the same procedure described above in equations (11)-(15), only for constant-liquidity values and returns instead of variable-liquidity values and returns, based on $\hat{V}_{it}^b$ instead of $\hat{P}_{it}$.[15]

To produce the supply side index the same type of simultaneous solution of (18) and (19) reveals that:

[15] It should be noted that buyers' side valuations will have a lower average value than the equilibrium transaction prices estimated in equation (11), as the central tendency of non-owners' valuations will lie below that of owners (previous selection causes owners, that is, previously successful buyers, having higher average valuations than non-owners), and therefore below the average transaction prices, which lie between potential buyers' and potential sellers' valuations. This will cause demand side (constant liquidity) total returns to have a tendency to be higher than the variable liquidity total returns, on average over the long run. (Recall that total returns include the income component, the cash flow as a fraction of property value. If the denominator, property valuation, is smaller, then this fraction will be larger, given that the annual income flow is an objective, exogenous value.) For this reason, a constant liquidity total return index is less clearly interpretable than a constant liquitidy price change (or capital value) index.

$$\hat{\alpha}^s = \hat{a} - \tfrac{1}{2}\hat{\sigma}\hat{\omega}$$

and: (22)

$$\hat{\beta}_t^s = \hat{\beta}_t - \tfrac{1}{2}\hat{\sigma}\hat{\gamma}_t .$$

The supply side reservation price value estimate for property *i* in period *t* is then:

$$\hat{V}_{it}^s = \hat{\alpha}^s A_{it} + \hat{\beta}_t^s \tag{23}$$

2. NCREIF Data and Index Estimation Procedure

Section 1 has laid out the fundamental theory and the general index construction methodology that underlies the variable liquidity transactions based index, including the extension to create demand and supply indices. In this section we describe at a more detailed level the NCREIF database and the specific estimation and index construction procedures we have employed.

Since its inception in 1982, the National Council of Real Estate Investment Fiduciaries (NCREIF) has been collecting quarterly income and value reports (in addition to other data, and starting with historical data since the end of 1977) for all the properties held for tax-exempt investors on the part of NCREIF's data-contributing member firms, which include almost all of the "core" real estate investment managers for pension funds in the U.S. This database is used to construct the NCREIF Property Index (NPI), the only property-level "benchmark" index of regular institutional commercial real estate investment performance in the U.S. The index reports quarterly total returns and capital appreciation and income return components. When the index begins in 1978 it includes 233 properties worth a total of $581,000,000. By 1984, the starting date of the transactions index, the NPI includes 1000 properties worth almost $10 billion. By 2005:4, the NPI covers 4712 properties worth in the aggregate about $190 billion. The database is well diversified by property type, and property type sub-indices are reported. The four major property types include office (26%), industrial (43%), apartment (20%), and retail (11%).[16]

In general, properties enter the index when they are at least 60% leased, and then remain in the index until they are sold.[17] Properties are generally reappraised at least once per year, on a staggered basis, so that some properties are reappraised every quarter. Property values are reported into the database every quarter for every property, but commonly value reports between reappraisals simply carry over the previous valuation (or else add only the book value of any capital improvements completed during the quarter). When properties are sold their last value reported in the database is the disposition sales transaction price.[18]

[16] Hotel properties make up less than 2% of the all-property index. The percentages reported here are calculated by number of properties, as represented in the 2005 database used in our index estimation.
[17] The index is meant to represent the investment performance of stabilized investment property operations, not development investments. Note also that the index is at the property level, excluding any effects of financing or fund management.
[18] Properties enter the database when they are acquired, or when their investment manager joins NCREIF. Often a property's first reported value in the database may be its acquisition transaction price, but necessarily and not always, and it is impossible to know whether or not a first reported value is a transaction price or an appraisal. Until recently, when a property was sold out of the database, its disposition transaction price was entered in the index in the quarter prior to its disposition. In constructing the transactions based index we control for this consideration so as to register transaction prices in the quarters in which the transactions were actually consummated (closed).

The TBI begins in 1984 because prior to then there was insufficient transaction frequency to form a reliable transactions-based index.[19] Since that time the NPI database has included over 9500 different properties, of which over 4500 have been sold. Of these, we are able to use 4572 sale transactions in estimating the hedonic price model. (Some sales must be dropped because they were of properties that were not held in the database long enough to obtain an independent appraisal estimate of their value, the primary explanatory variable in the hedonic price model.) Altogether, we have observations of 142,973 property-quarters, counting each property times each quarter it is in the database, including properties in quarters when they are not sold. This pooled database is the source of our estimation of the probit sales model, as well as the TBI.

The first step in building the TBI is to estimate the selection-corrected hedonic price model specified in equation (10), based on the sold property sample in the NPI database. Before turning to estimation of this model at the quarterly frequency, we first estimate it at the annual frequency. The results of estimating this annual model provide necessary information for our econometric procedure for dealing with "noise" in the quarterly model. In the annual case, we have on average about 200 price observations per period. This model is estimated simultaneously for all properties and for each of the four property types using a "stacked" specification with property-type dummy variables estimated on all 4572 transactions. Based on experience from previous studies, the dependent variable has been defined as the log price per square foot of building area. As noted in Section 1, the anchor explanatory variable is based on an extension of the Clapp & Giacotto (1992) "assessed value method." However, unlike Clapp and Giacotto's

[19] The property type specific sub-indices must begin even later (for the same data sufficiency reason), in 1994.

"assessed values", our "appraised values" are updated regularly, such that we are able to use appraisals just prior to the transaction sales as our composite hedonic variable. In particular, we use the log of the value per square foot reported by NCREIF *two quarters prior* to the transaction sale. This was found to be necessary to ensure that the explanatory variable is independent of the dependent variable (transaction price). As noted in Section 1, the result is that the time dummy coefficients in the model represent the difference each period between the (lagged) appraisals and the transaction prices.[20]

The price model specification includes some additional "hedonic" type explanatory variables besides the appraised value. It includes 18 metropolitan area dummy variables (the omitted "base case" is Los Angeles.) Also included are property type dummy variables for ten sub-categories within the four major property types: apartment, office, industrial, and retail. Keep in mind that in principle there is no reason why additional property-specific location and property characteristic variables beyond the composite hedonic variable labeled A_{it} (recent appraisal) cannot be incorporated into the hedonic price model. Going back to the underlying reservation price models in equations (1) and (2), such additional hedonic variables would be components of the j-dimensional X_{ijt} hedonic vector that are not adequately captured in the composite hedonic variable A_{it}. The annual model results are presented at http://web.mit.edu/cre/research/credl/tbi.html. The specification is

[20] In order to reduce temporal aggregation bias that results from averaging sale prices over the calendar year (see Geltner 1993, 1997), in the case of annual frequency estimation of the price model we have modified the Bryan & Colwell (1982) definition of time-dummy variables (to apply to a hedonic model instead of a repeat-sale model). Thus, at the annual frequency our time-dummy variables are defined as follows: For a sale in the *q-th* calendar quarter of year t, the time-dummy for year t equals $1 – (4\text{-}q)/4$ and the time-dummy for year $t\text{-}1$ equals $(4\text{-}q)/4$. No modification is made for quarterly frequency estimation, as we have no information on when, within each quarter, the sale takes place. It should also be noted that, in principle colinearity between the time dummy variables and the appraised values could affect the index. However, this appears not to be a problem. We found little correlation between the time-dummies and the appraised values, and separate estimation of the annual frequency index on each individual year's transactions produced a result very similar to the pooled estimation.

the same as for the quarterly model presented in Appendix B, except that it has annual, not quarterly, time dummies.

The annual results are corrected for transaction sample selection bias using the standard Heckman (1979) two-step procedure described in Section 1. Again, the specification of the 1st-stage probit selection model (corresponding to equation (9) is the same as the quarterly specification presented in Appendix B, except that it has annual, not quarterly, time dummies. This model of property sale probability includes as explanatory variables the appraised value composite hedonic variable, the dummy variables for metropolitan area and property subtype, and the time dummy variables necessary for constructing the constant liquidity index [the A_{it} and Z_t variables of equation (9)]. This model also includes building size (square feet), and a constant term.

While the annual selection model performs well as a model of property sales probability, the selection bias indicator variable, "lambda", is not significantly different from zero. (See http://web.mit.edu/cre/research/credl/tbi.html.) Indeed, when we compare the representative property index based on the selection-corrected price model with a similar representative property index based on the simple OLS price model without sample selection bias correction, the two indices are almost identical. Thus, in contrast to findings in the previous literature on commercial property transactions based indices, sample selection bias does not appear to be an issue with our annual model specification.[21] On the other hand, the probit model contains some interesting results

[21] See Munneke & Slade (2000, 2001), and FGGH (*op.cit.*). Apparently, the appraised value composite hedonic explanatory variable is able to capture the effect of most differences between the sold and unsold property samples much more effectively than the specifications used in the previous research. Some insight into this result may be suggested by the finding in Fisher, Gatzlaff, Geltner, & Haurin (2004) that a

regarding sales characteristics in the NCREIF database. The strongly significant and negative coefficients on both the appraised value/SF and the square foot variables suggests that not only do larger properties sell less frequently, but also “higher quality” properties (as indicated by higher appraised value per square foot).

The next step in transaction price index development is to construct a longitudinal price index based on the hedonic price model. Here we use the “representative property” method defined in equation (12a). The representative property for a given year is calculated by computing the mean characteristics (size, property type, MSA) of all the properties in the NCREIF data base in that year. This computation is carried out for every year, reflecting the changing composition of the NCREIF member holdings. This makes our indexes with the income component of returns more accurate because the method we are using to determine income returns is based on the NCREIF computation of income returns. We use these mean characteristics in our pricing model to determine the variable liquidity (VL) valuation, and, thus, the variable liquidity returns (computed using the same representative property at the beginning and end of the period).

To determine the A_{pt} log lagged appraised value composite hedonic variable for the representative property, we start out with the average appraised value per square foot of all properties in the first year of our index, and grow this value at the NPI equal-weighted cash flow based capital returns rate.[22]

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property’s current appraised value relative to NPI growth since acquisition (their “WINS” variable) was a predictor of sale likelihood.

[22] We use the equal-weighted version of the NPI to define the “representative property” as the “mean” or “average” property in the index. We use the cash flow based definition of appreciation return so as to include the effect of capital improvement expenditures in the capital appreciation of the index. This makes the NPI a property *value change* index (where value changes reflect both capital improvements as well as market changes). Later, in constructing a total return index, we must be consistent and use the cash flow

A cumulative appreciation (or capital growth) value level index can then be constructed by compounding the annual appreciation returns, starting from an arbitrary initial value. This can be compared to the NPI appreciation value index (equal-weighted, cash flow based) over the same period.[23] The transaction based index is slightly more volatile than the NPI, and appears to slightly lead the NPI in time, with major turning points occurring one to three years earlier.

It is important to note that the annual frequency index does not show any evidence of random estimation error “noise”. The index has low annual return volatility (5.5%), reasonable first-order autocorrelation in the returns (+35%), and a relatively “smooth” appearance in levels. All of these are characteristics of an absence of noise.

The next step in creating the TBI is to move from the annual frequency model to quarterly frequency. This step, of course, results in a reduction by a factor of four in the average number of sales transaction observations per period, to less than 50 transactions on average per quarter. This results in a problem of estimation error “noise” in the index.. This gives the quarterly index a “spiky” appearance, especially during the earlier history when there were fewer transaction observations.

To address the noise problem at the quarterly frequency, we employ an extension of the Bayesian noise filtering technique developed by Goetzmann (1992), Gatzlaff and Geltner (1998), and Geltner and Goetzmann (2000). This technique involves the use of a ridge regression as a Method of Moments estimator. The estimator minimizes the squared

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based NPI income return component (net of capital improvement expenditures) to define the representative property’s income.

[23] As the starting value of each index is arbitrary, the indices are set so that they have equal average value levels across the entire history.

errors of the predicted values (property prices) subject to moment restrictions in the results. The moment restrictions, characterizing the return time series statistics of the resulting estimated index, are based on *a priori* information about the nature of the results that should obtain. In the present case, the moment restrictions are employed as a “noise filter”. The ridge procedure eliminates noise in the estimated index without inducing a temporal lag in the index returns. In the present context the moment restrictions are defined to produce a quarterly index whose annual end-of-year return time-series characteristics approach those of the manifestly noise-free annual index, which was estimated at the annual frequency, classically, without the Bayesian filter. The mechanics of applying the ridge procedure are described in Appendix A.

We use three criteria in deciding when the moment restrictions are met. The first two criteria are quantitative moment comparisons between the quarterly index and the index estimated at the annual frequency. First, we compare the annual volatility of the quarterly index (based on its end-of-year returns) to that of the annual index. Second, we compare the annual first-order autocorrelation of the two indices (again basing this on end-of-year annual returns for the quarterly index). Our third criterion is qualitative. We look at the resulting annualized (based on ends of years) quarterly index and compare it visually to the annual index. We select the lowest value of k for which all three of these criteria show a close similarity between the annualized quarterly index and the noise-free (and ridge-free) annual index.[24].

To the best of our knowledge, the ridge regression technique has not previously been used simultaneously with the Heckman selection correction procedure. The

[24] The same procedure is applied separately to each of the property sector sub-indices.

complication involved becomes apparent when you consider that from the point of view of the Heckman selection procedure, there are “extra” observations in the second-stage price equation (one for each quarter) as a result of using a ridge technique. We proceed as follows: First, the probit probability of sale model is estimated. These results are used to construct the inverse Mills ratio for use in the price equation (instead of simply running a packaged two-stage Heckman procedure). For each of the synthetic quarterly observations in the price equation, we use the mean of all values of the inverse Mills ratio vector that fall in that respective quarter. This allows us to estimate the price equation with a value of the inverse Mills ratio for each observation.

The final step in the construction of the TBI is the inclusion of income to quantify the total return each period. This is done in a manner analogous to the construction of the representative property capital returns from the NPI, only now we use the NPI income returns as well. The general formula for computing the representative property transaction based total return, r_{pt} , is:

$$\left(1+r_{pt}\right)=\left(\exp\left[\hat{P}_{pt}\right]+CF_{pt}\right)\Big/\exp\left[\hat{P}_{pt-1}\right] \tag{24}$$

Where CF_{pt} is derived for the representative property by applying the NPI (equal-weighted cash-flow based) income yield in quarter t to the representative property value level as of the end of quarter $t-1$ (which in turn is based on the accumulation of the NPI equal-weighted cash-flow based capital returns, as described above). Thus, the amount CF_{pt} gives the representative property the same appraisal-based income yield in period t as the NPI, based on the representative property’s hedonic value.

Construction of transaction based representative property demand (constant liquidity) and supply side indices proceeds exactly as above, only based on $\hat{V}_{pt}^{b}$ and $\hat{V}_{pt}^{s}$ as described in equations (21) and (23).

Most of the difference in the returns between the variable-liquidity transactions based index and the demand and supply side indices will result from the probit time-dummy coefficients, $\hat{\gamma}_t$. These coefficients mirror the transaction frequency in the NCREIF property population. Unfortunately, this transaction frequency appears to be excessively random at the quarterly frequency. (Notice the "spiky" appearance in Exhibit 2.) Conversation with NCREIF members suggests that the specific quarterly timing of the recording of sales transactions is somewhat random, following a due-diligence and administrative process of scheduling the transaction closing, some time after the deal has been essentially agreed upon. The random and lagged nature of quarterly transaction report timing may be a source of noise in the quarterly price model, and may also result in a lagging phenomenon within the transaction price index. In constructing the demand and supply side indices at the quarterly frequency we have endeavored to mitigate this problem to some extent by employing a semi-annual averaging of the probit time-dummy coefficients. Exhibit 3 portrays the thusly-averaged coefficients superimposed on the variable-liquidity transaction price log levels.

Insert Exhibits 2 & 3 about here.

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3. Results and Analysis

Application of the procedures described in Section 2 results in the noise-filtered transactions based representative property cumulative quarterly appreciation index shown in Exhibit 4 together with the quarterly NPI. (The index in Exhibit 4 is labeled "VL", for variable-liquidity, to distinguish it from the constant-liquidity version presented below.) Note that the transactions based index exhibits greater volatility than the NPI, and appears to slightly lead the NPI in major turning points. There is evidence that the volatility is real, in that particular historical events that would be expected to have negatively affected real estate markets are indeed reflected in depressions or down-ticks in the transactions based index (as shown in the exhibit). These historical events do not much appear in the NPI. The detailed model estimation results corresponding to Equations (9) & (10) are presented in Appendix B. [25]

Insert Exhibit 4 about here.

Quarterly property-type sub-indices are also constructed for office, industrial, apartment, and retail (http://web.mit.edu/cre/research/credl/tbi.html). Due to transaction data scarcity at the property-type level, these indices begin in the early 1990s, even using the ridge regression noise filter described previously.

[25] Note that the price model has an R^2 over 99.9%, while the probit sales model has a pseudo-R^2 of only 0.05. However, it must be recognized that we have N=142,973 observations, with only 4,572 sales transactions, making it difficult to obtain a high pseudo-R^2 in a selection model. (By way of comparison, with a much larger sales proportion in their annual-frequency data, Fisher *et al* (2004) obtain a maximum pseudo-R^2 of only slightly over 0.12 in a model that was focused explicitly on optimizing the sales prediction.)

Exhibit 5 returns us to the 20-year, all-property sample, and depicts the demand side (constant liquidity) and supply side transaction based indices at the quarterly frequency. The demand side index tends to move a bit farther or more quickly than the supply side index, consistent with pro-cyclical variable liquidity. The difference in returns implied by the difference in the demand side, constant liquidity index and the variable liquidity index narrows as transaction volume increases and widens as transaction volume decreases.

Insert Exhibit 5 about here.

To begin to explore the investment policy significance of the transaction based indices developed here, we have examined the quarterly total return statistics at the all-property level in comparison with those of other major asset classes. Exhibit 6 presents a summary of the major quarterly total return time series statistics for the NPI and the TBI (variable-liquidity), along with several other major investment asset classes and indicators. Included are: (i) The NAREIT Equity REIT Index; (ii) the S&P500 Large Cap Stock Index; (iii) The Ibbotson Small Cap Stock Index; and (iv) The Ibbotson Long-Term U.S. Government Bond Index. The table reports the quarterly arithmetic mean total returns, quarterly volatility, Sharpe Ratio, and 1st-order autocorrelation coefficients for each asset class or series, as well as the cross-correlation among the series.

Insert Exhibit 6 about here.

It is interesting to note that while the TBI has notably higher volatility at the quarterly frequency and lower autocorrelation than the appraisal-based NPI, its volatility is still less than that of the stock and bond asset classes and its 1st-order autocorrelation is comparable. Also, while the TBI has higher correlation with both REITs and the stock market asset classes than the NPI does, its correlations with stocks is still low in absolute terms as well as relative to other securities based asset classes.

The result is that even when we use the TBI to represent private real estate, the role of private real estate is still prominent in a classical Markowitz mean-variance portfolio optimization, or a Sharpe-Maximizing (CAPM "Market Portfolio" type) efficient frontier analysis, based on historical investment performance statistics over the 1984-2005 period covered in our analysis. Exhibits 7 and 8 present area charts for the efficient frontier of risky assets as a function of target return (on the horizontal axis), with real estate measured either by the NPI (Exhibit 7) or the TBI (Exhibit 8). We see that even using the transactions based index, private real estate plays a large role in the optimal portfolio, especially in the more conservative (lower return target, lower risk) range of investment policy. The difference in the optimal portfolio allocations shown in the area charts is small between the NPI and the TBI. Exhibit 9 shows that the Sharpe-Maximizing portfolio allocation gives a large role to private real estate, though considerably less based on the TBI than based on the NPI.[26]

[26] The risk-free interest rate is defined as the historical quarterly return earned by 30-Day Treasury Bonds during the period in question: 1984-2005. It should be noted that the mean return to the NPI during the historical period used in this analysis, 1.86%, was substantially below that of the broader period since the NPI inception in 1978 through 2004, which is 2.33%.

Insert Exhibits 7-9 about here.

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4. Conclusion

This paper has presented a new type of institutional investment real estate index, the TBI, based on transaction prices and designed to support research on investment performance and asset market movements. The results provide interesting and useful information to the academic and industry research communities, contributing to the objective of improving the level and quality of understanding and decision making in the real estate investment industry.

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Exhibit 1: Evolution of Buyer & Seller Reservation Price Distributions reflecting Variable Turnover.

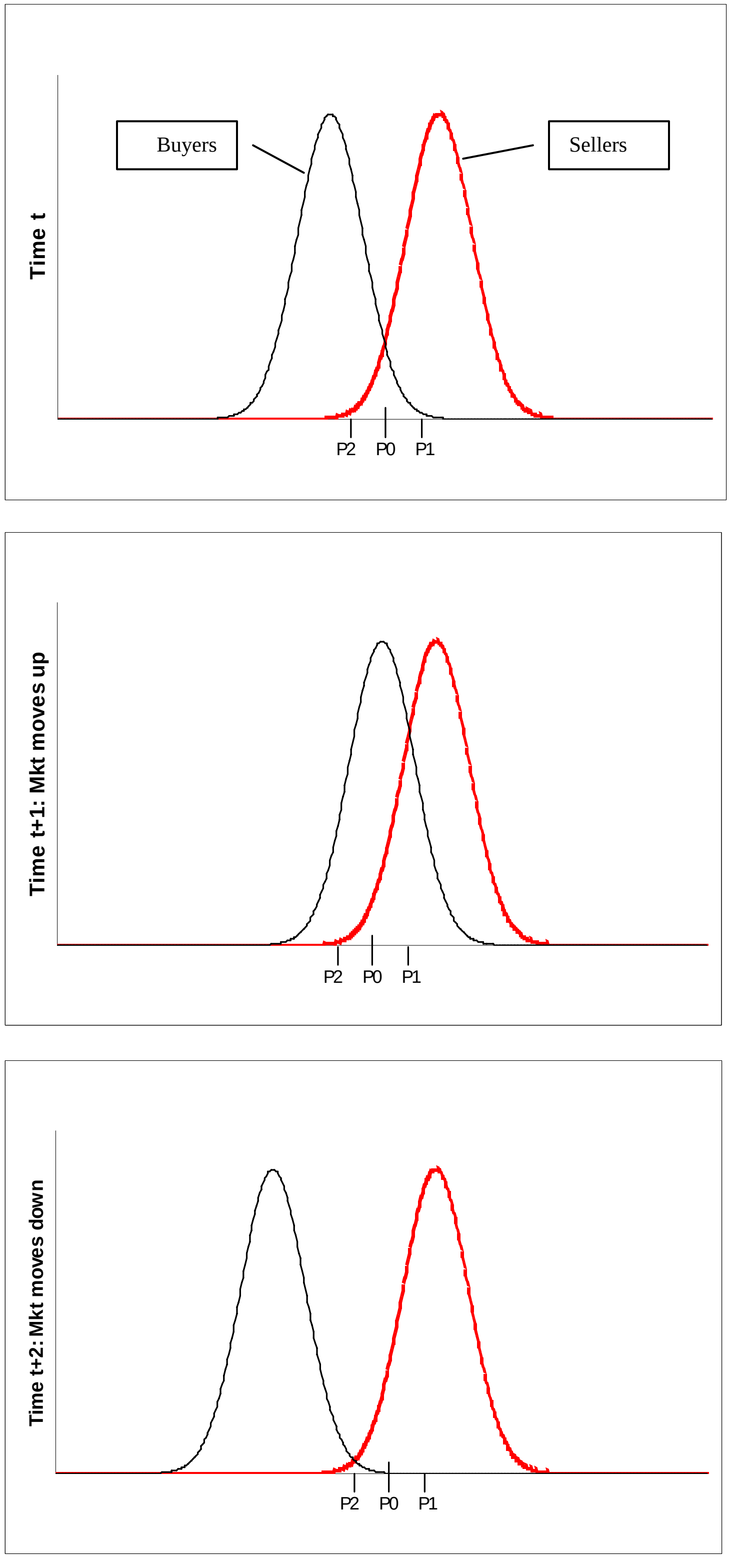


Exhibit 2: Quarterly All-property Probit Time-Dummy Coefficients (relative to average), Tracing Relative Frequency of Property Sales Transactions in the NCREIF Database

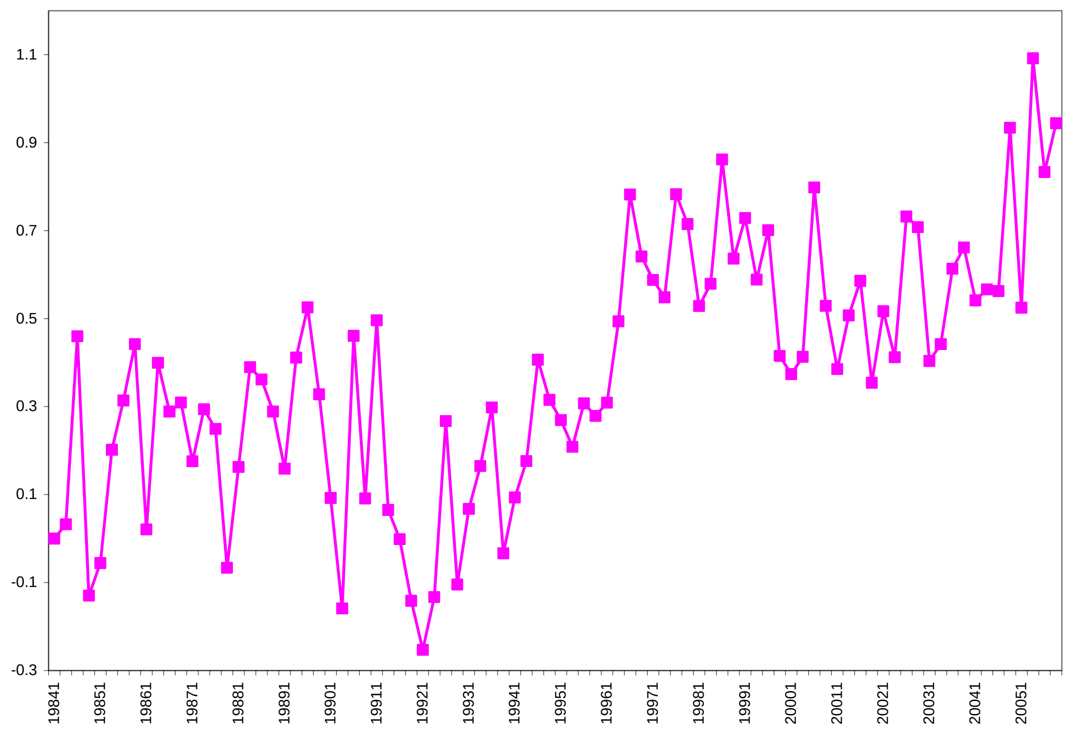


Exhibit 3: Semi-Annual Averaged Probit Time-Dummy Coefficients Superimposed on NCREIF Transaction Price Log Levels

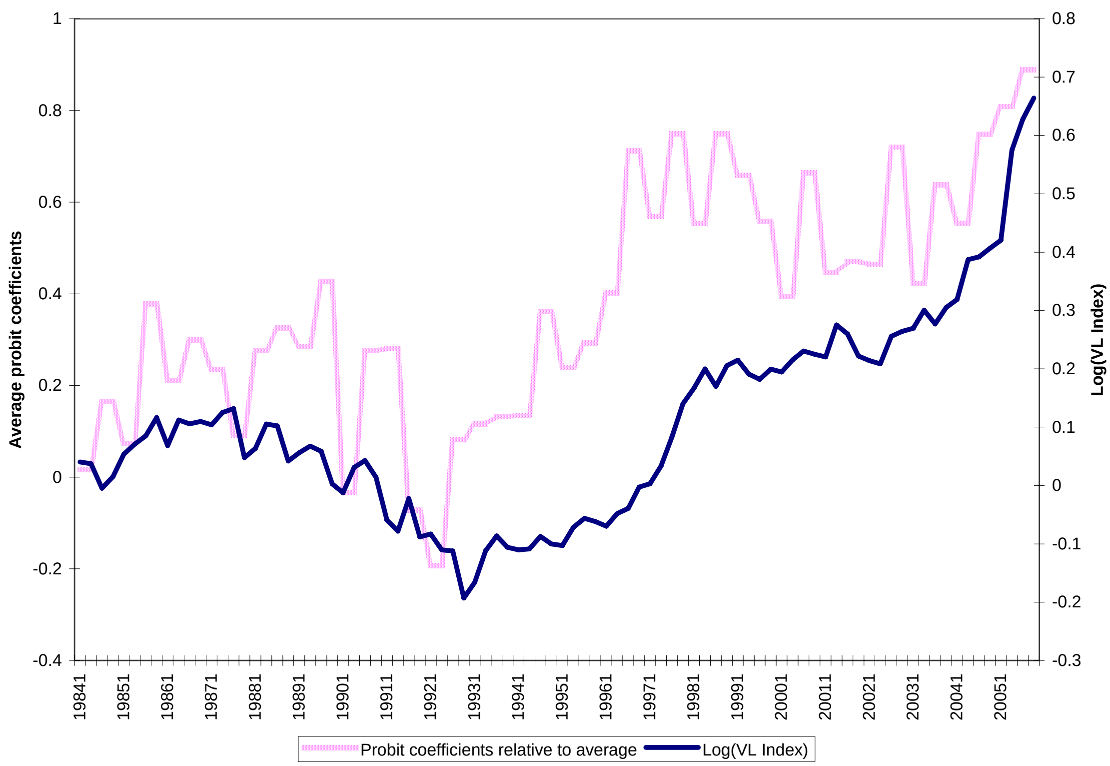


Exhibit 4: Quarterly Appreciation Levels, TBI vs NPI:

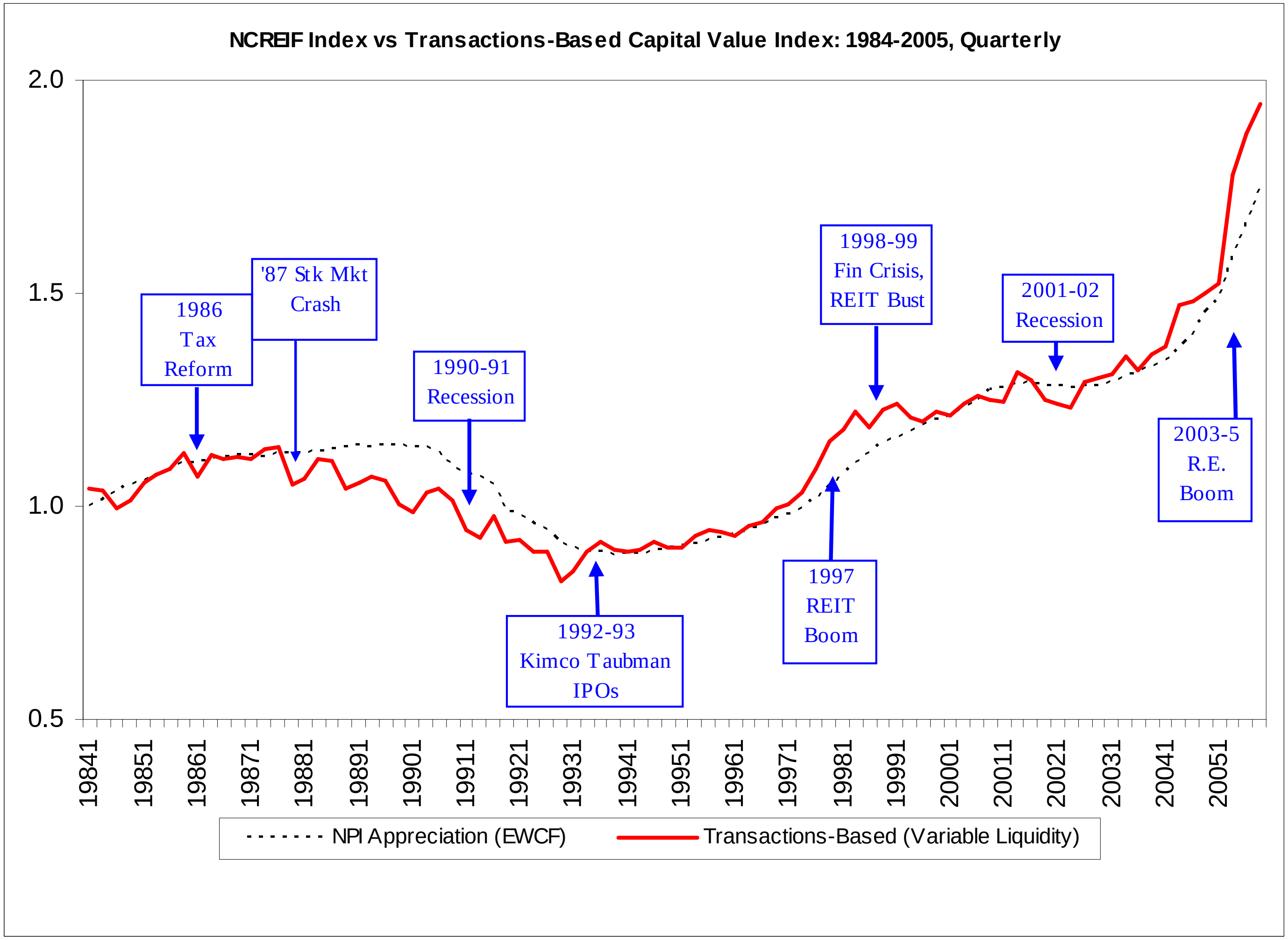


Exhibit 5: Supply and Demand Indexes

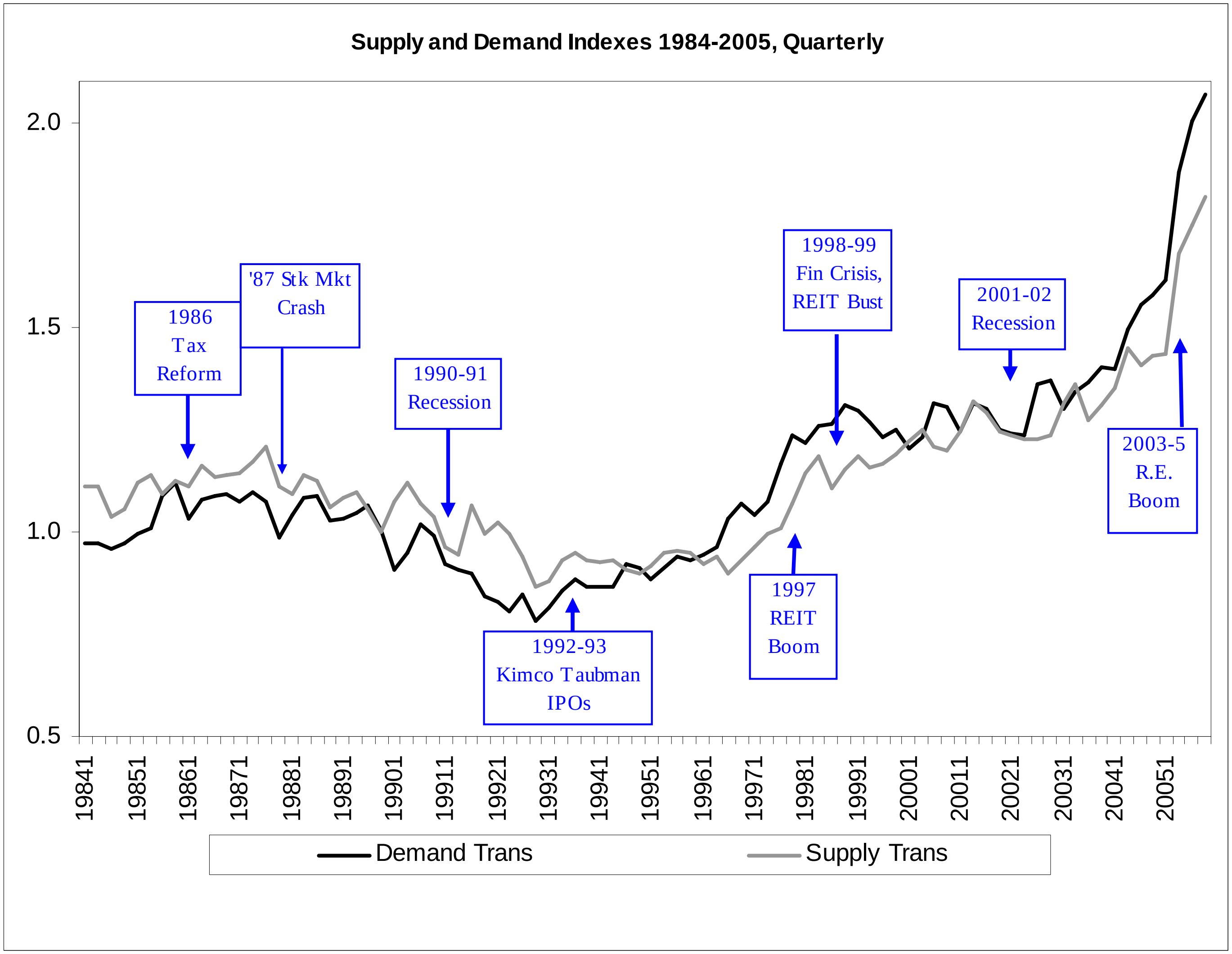


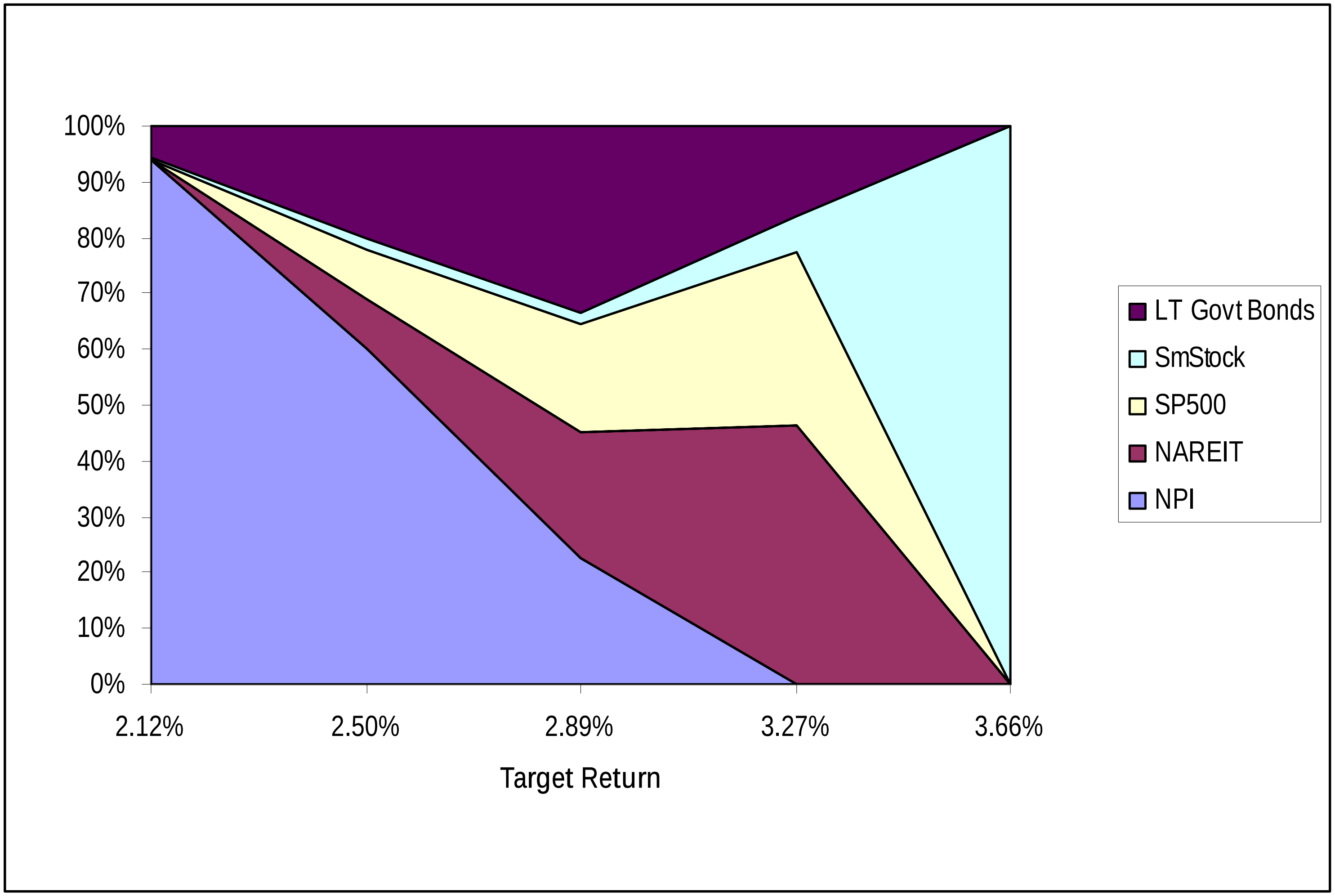
Exhibit 6

Quarterly Total Return Statistics 1984Q2-2005Q4

	NPI	Var.Liq.Trans.	NAREIT	SP500	SmStock	LT Govt Bonds
Mean	2.12%	2.25%	3.32%	3.37%	3.66%	2.79%
Std.Dev.	1.68%	3.63%	6.86%	8.02%	11.18%	5.25%
Autocorr	79.53%	8.65%	-1.51%	-6.06%	-20.72%	-1.43%
Sharpe	0.54	0.29	0.31	0.27	0.22	0.30

Correlations:	NPI	Var.Liq.Trans.	NAREIT	SP500	SmStock	LT Govt Bonds
NPI	100.00%	56.40%	5.51%	1.38%	-1.72%	-4.29%
Var.Liq.Trans.		100.00%	11.75%	12.58%	10.94%	0.14%
NAREIT			100.00%	47.41%	60.79%	23.52%
SP500				100.00%	78.29%	3.69%
SmStock					100.00%	-8.92%
LT Govt Bonds						100.00%

Exhibit 7: Optimal Portfolio Shares, with Private Real Estate based on NPI



(Quarterly target return on horizontal axis.)

Exhibit 8: Optimal Portfolio Shares, with Private Real Estate based on the TBI

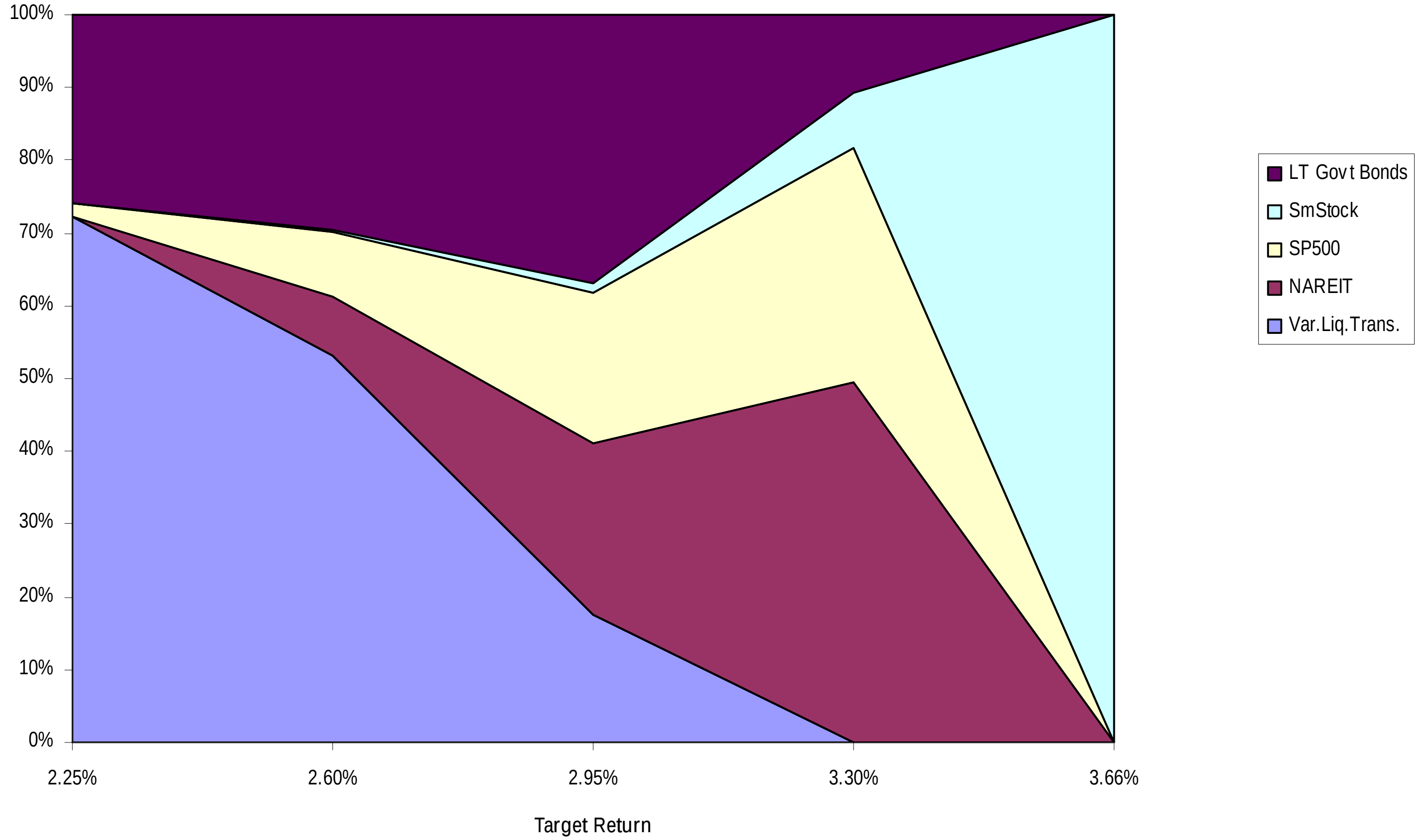


Exhibit 9: Sharpe-Maximizing Optimal Portfolio Shares under Two Different Private Real Estate Scenarios

Sharpe Maximizing Portfolios:		
NPI	77%	NA
TBI	NA	43%
NAREIT	3%	12%
SP500	4%	12%
SmStock	2%	1%
LT Govt Bonds	14%	32%

Appendix A

Mechanics of Applying the Ridge Regression Procedure

The ridge regression procedure works mechanically by adding "synthetic data" to the estimation database. Specifically, we add one "observation" for each of the 92 quarters. As noted, the synthetic data is based on the annual frequency version of the price model. The effect of the synthetic data is to "pull" the quarterly results toward the smoother (presumably noise-free) annual results. The strength of this "pull" which dampens random noise is inversely related to the number of actual price observations in the real data for each period of time. The ridge effect is adjusted by means a parameter, labeled *"k"*, which governs the strength of the synthetic data in the estimation process. Each of the 92 rows of synthetic data is multiplied by *k*. The higher the k, the greater the influence the added observations have on the regression results.

For each quarter, a row of synthetic data is constructed as follows. The LHS dependent variable price observations are taken directly from the annual frequency transaction index, with quarterly values linearly interpolated between the annual end-of-year levels. The RHS synthetic A_{it} composite hedonic variable values are similarly constructed from the NPI appreciation index, only lagged two quarters. Each row of synthetic data corresponds to one quarter of calendar time, and therefore has one time dummy variable equal to unity, corresponding to the quarter represented by the row. Thus, the time dummies in the synthetic data make a diagonal square matrix of ones. (The constant and time-invariant dummy variables are also included in the ridge at their population mean levels.)

Appendix B

Estimation Results for Quarterly All-Property Model (Equations 9 & 10)

Heckman 2nd Step: Price model
Dependent Variable: Log of Sale Price per Square Foot

	Coefficient	Std. Error	t
aptgard_dum	0.023	0.011	2.075
apthigh_dum	0.030	0.025	1.197
regionalmall_dum	0.088	0.031	2.850
retailmall_dum	-0.062	0.025	-2.462
retailsingle_dum	0.037	0.021	1.736
warehouse_dum	0.003	0.010	0.252
indrd_dum	-0.014	0.013	-1.044
indflex_dum	-0.006	0.020	-0.314
offcbd_dum	0.006	0.014	0.423
offsub_dum	-0.002	0.009	-0.179
LogHedonic	1.016	0.006	173.994
Other City	-0.042	0.014	-3.089
IL-Chicago	-0.038	0.017	-2.303
TX-Dallas	-0.047	0.018	-2.589
DC-Washington	-0.001	0.018	-0.077
GA-Atlanta	-0.038	0.019	-2.077
CA-Orange County	0.000	0.021	0.003
CA-San Jose	-0.029	0.024	-1.212
AZ-Phoenix	-0.007	0.020	-0.374
TX-Houston	-0.013	0.020	-0.655
MN-Minneapolis	-0.043	0.021	-2.060
WA-Seattle	0.001	0.022	0.055
CO-Denver	-0.038	0.021	-1.783
MA-Boston	-0.030	0.022	-1.373
CA-Oakland	0.010	0.025	0.399
PA-Philadelphia	-0.023	0.024	-0.976
CA-San Diego	0.005	0.023	0.200
MO-Saint Louis	-0.048	0.026	-1.830
MD-Baltimore	-0.004	0.025	-0.175
19842	-0.020	0.044	-0.456
19843	-0.077	0.040	-1.932
19844	-0.075	0.045	-1.643
19851	-0.049	0.045	-1.092
19852	-0.043	0.043	-1.006
19853	-0.042	0.041	-1.009
19854	-0.025	0.040	-0.618
19861	-0.080	0.044	-1.811
19862	-0.041	0.041	-1.001
19863	-0.053	0.042	-1.265
19864	-0.052	0.042	-1.248
19871	-0.061	0.043	-1.425

19872	-0.038	0.041	-0.925
19873	-0.034	0.042	-0.817
19874	-0.122	0.045	-2.725
19881	-0.107	0.043	-2.511
19882	-0.068	0.040	-1.698
19883	-0.074	0.040	-1.836
19884	-0.138	0.041	-3.359
19891	-0.129	0.043	-3.038
19892	-0.117	0.040	-2.940
19893	-0.128	0.039	-3.274
19894	-0.186	0.041	-4.539
19901	-0.197	0.043	-4.588
19902	-0.152	0.045	-3.343
19903	-0.135	0.040	-3.411
19904	-0.144	0.043	-3.350
19911	-0.195	0.039	-4.960
19912	-0.202	0.043	-4.713
19913	-0.131	0.044	-2.996
19914	-0.160	0.045	-3.562
19921	-0.122	0.046	-2.668
19922	-0.130	0.044	-2.966
19923	-0.111	0.039	-2.811
19924	-0.166	0.043	-3.833
19931	-0.119	0.042	-2.836
19932	-0.054	0.041	-1.315
19933	-0.020	0.039	-0.512
19934	-0.036	0.043	-0.839
19941	-0.038	0.041	-0.909
19942	-0.037	0.040	-0.923
19943	-0.020	0.038	-0.518
19944	-0.041	0.039	-1.051
19951	-0.053	0.040	-1.340
19952	-0.029	0.040	-0.719
19953	-0.019	0.040	-0.475
19954	-0.032	0.040	-0.797
19961	-0.050	0.040	-1.260
19962	-0.037	0.038	-0.978
19963	-0.037	0.036	-1.038
19964	-0.017	0.037	-0.452
19971	-0.028	0.037	-0.737
19972	-0.008	0.037	-0.209
19973	0.024	0.036	0.680
19974	0.055	0.037	1.483
19981	0.053	0.039	1.376
19982	0.060	0.038	1.596
19983	0.008	0.036	0.219
19984	0.024	0.038	0.644
19991	0.016	0.037	0.438
19992	-0.020	0.038	-0.538
19993	-0.042	0.037	-1.129

19994	-0.036	0.039	-0.922
20001	-0.053	0.040	-1.342
20002	-0.045	0.039	-1.138
20003	-0.043	0.036	-1.205
20004	-0.065	0.038	-1.719
20011	-0.081	0.039	-2.063
20012	-0.036	0.038	-0.943
20013	-0.056	0.037	-1.493
20014	-0.091	0.039	-2.295
20021	-0.094	0.038	-2.481
20022	-0.097	0.039	-2.515
20023	-0.050	0.039	-1.304
20024	-0.044	0.039	-1.133
20031	-0.043	0.039	-1.113
20032	-0.019	0.038	-0.509
20033	-0.052	0.036	-1.430
20034	-0.034	0.036	-0.930
20041	-0.030	0.037	-0.804
20042	0.021	0.037	0.577
20043	0.004	0.037	0.112
20044	-0.010	0.035	-0.274
20051	-0.028	0.037	-0.747
20052	0.088	0.034	2.575
20053	0.080	0.035	2.250
20054	0.067	0.035	1.923
_cons	0.028	0.043	0.641
InvMills	-0.003	0.004	-0.722
Adjusted R^2	0.999		
N	4654		

CA-Los Angeles is used as the omitted case for city dummies

Heckman 1st Step: Selection Model

	Coefficient	Std. Error	t
LogHedonic	-0.369	0.015	-25.084
Other City	-0.128	0.032	-4.02
IL-Chicago	-0.111	0.039	-2.861
TX-Dallas	-0.199	0.042	-4.733
DC-Washington	0.048	0.042	1.153
GA-Atlanta	-0.172	0.043	-3.953
CA-Orange County	-0.03	0.048	-0.63
CA-San Jose	-0.093	0.054	-1.728
AZ-Phoenix	-0.089	0.047	-1.879
TX-Houston	-0.162	0.048	-3.346
MN-Minneapolis	-0.151	0.05	-3.049
WA-Seattle	-0.117	0.05	-2.337
CO-Denver	-0.117	0.05	-2.337
MA-Boston	-0.048	0.051	-0.945
CA-Oakland	-0.169	0.056	-2.994
PA-Philadelphia	-0.083	0.057	-1.464
CA-San Diego	0.045	0.056	0.808
MO-Saint Louis	-0.138	0.061	-2.269
MD-Baltimore	-0.019	0.059	-0.317
aptgard_dum	-0.266	0.026	-10.307
apthigh_dum	-0.149	0.059	-2.506
regionalmall_dum	0.059	0.072	0.817
retailmall_dum	-0.071	0.062	-1.152
retailsingle_dum	-0.55	0.05	-10.919
warehouse_dum	-0.439	0.025	-17.926
indrd_dum	-0.214	0.031	-6.944
indflex_dum	-0.453	0.047	-9.664
offcbd_dum	0.012	0.034	0.357
offsub_dum	-0.057	0.022	-2.615
sqft	0	0	-7.865
_cons	-0.471	0.14	-3.377
19842	0.031	0.161	0.194
19843	0.464	0.142	3.266
19844	-0.128	0.174	-0.734
19851	-0.057	0.169	-0.336
19852	0.206	0.153	1.347
19853	0.319	0.147	2.175
19854	0.45	0.143	3.151
19861	0.025	0.164	0.153
19862	0.408	0.145	2.807
19863	0.295	0.149	1.978
19864	0.315	0.148	2.123
19871	0.185	0.154	1.201
19872	0.301	0.146	2.056
19873	0.259	0.148	1.746
19874	-0.06	0.166	-0.358

19881	0.172	0.152	1.135
19882	0.399	0.142	2.806
19883	0.37	0.142	2.598
19884	0.297	0.145	2.051
19891	0.171	0.15	1.137
19892	0.422	0.141	3.003
19893	0.537	0.137	3.906
19894	0.343	0.143	2.389
19901	0.101	0.154	0.657
19902	-0.151	0.171	-0.879
19903	0.474	0.138	3.425
19904	0.103	0.153	0.672
19911	0.509	0.138	3.685
19912	0.075	0.152	0.494
19913	0.006	0.156	0.036
19914	-0.134	0.164	-0.819
19921	-0.244	0.17	-1.437
19922	-0.128	0.156	-0.819
19923	0.274	0.138	1.983
19924	-0.098	0.154	-0.638
19931	0.074	0.146	0.505
19932	0.17	0.142	1.198
19933	0.304	0.138	2.201
19934	-0.024	0.149	-0.162
19941	0.104	0.144	0.723
19942	0.185	0.14	1.321
19943	0.418	0.134	3.107
19944	0.328	0.137	2.391
19951	0.284	0.139	2.047
19952	0.226	0.141	1.604
19953	0.323	0.138	2.342
19954	0.299	0.139	2.146
19961	0.33	0.138	2.385
19962	0.514	0.134	3.837
19963	0.804	0.129	6.211
19964	0.666	0.131	5.077
19971	0.62	0.132	4.689
19972	0.58	0.133	4.364
19973	0.815	0.13	6.284
19974	0.753	0.131	5.725
19981	0.568	0.136	4.175
19982	0.621	0.134	4.65
19983	0.906	0.129	6.998
19984	0.679	0.133	5.101
19991	0.773	0.131	5.881
19992	0.636	0.134	4.752
19993	0.752	0.132	5.711
19994	0.462	0.137	3.366
20001	0.424	0.137	3.083
20002	0.463	0.136	3.402

20003	0.85	0.13	6.559
20004	0.581	0.134	4.349
20011	0.432	0.137	3.16
20012	0.562	0.134	4.201
20013	0.639	0.131	4.861
20014	0.403	0.136	2.96
20021	0.567	0.133	4.277
20022	0.462	0.134	3.442
20023	0.782	0.137	5.724
20024	0.76	0.137	5.561
20031	0.451	0.134	3.363
20032	0.49	0.133	3.688
20033	0.663	0.129	5.126
20034	0.711	0.129	5.517
20041	0.59	0.131	4.516
20042	0.615	0.13	4.732
20043	0.61	0.13	4.7
20044	0.98	0.126	7.751
20051	0.573	0.131	4.384
20052	1.133	0.126	9.01
20053	0.888	0.128	6.948
20054	0.998	0.127	7.847
Pseudo R^2	0.05		
N	142973		

CA-Los Angeles is used as the omitted case for city dummies

A Simplified Transactions Based Index (TBI) for NCREIF Production

by
David Geltner
MIT Center for Real Estate & Geltner Associates LLC
May 2, 2011

Summary:

This paper reviews the original TBI as it has been produced at MIT from 2006 through 2010, and explores a simplified average-price-based alternative version for possible NCREIF production and publication, including detailed operating instructions for such production.

The paper first briefly describes in relatively non-technical terms the nature and role of the “transactions based index” (TBI) that the MIT Center for Real Estate, with NCREIF cooperation, has been producing and publishing quarterly for five years based on sales of properties from the NCREIF Property Index (NPI) database. A transactions based index such as the TBI is seen to be useful as a *complement* (not substitute) for the appraisal-based NPI. It is noted that during the past five years the TBI has in fact gained a substantial user constituency in academia, industry, and government.

In this paper a simplified methodology is proposed for producing a TBI without using regression analysis. The simplified method is based on the average ratio each quarter of the sale price divided by the recent prior appraisal for the properties sold from the NPI database. This index construction method can be implemented in Excel without specialized statistical software or knowledge. This version of the TBI is more amenable to NCREIF production, and may also appear more transparent to a non-academic practitioner community. It is therefore likely to be more commensurate with ease of communication to industry researchers. In the present paper this simplified TBI is labeled “NTBI”, for “NCREIF” version, to distinguish it from what is here labeled the “MTBI” for the pre-existing “MIT” version.

This paper compares the recent historical results of the NTBI with the MTBI. It is found that the NTBI works well and very closely replicates the MTBI at the aggregate all-property level. For producing sector level transactions based indices (separate indices of apartment, industrial, office, and retail market segments, or conceivably other such breakouts or sub-indices, such as geographic regions) it is recommended here that the transaction/appraisal differences be based on the all-property sample of sold properties, pooled across all of the sectors. This differs from the way the sector-level MTBI indices were produced. But in fact the MTBI sector indices have suffered from small transaction samples, and the recommended NTBI sector index procedure here is based on the reasonable assumption that transaction/appraisal differences do not tend to vary systematically across sectors.

The only major loss in a replacement of the MTBI by the proposed NTBI would be the Demand and Supply indices that have been being produced at MIT, and that are based necessarily on regression models. These indices are particularly useful for market diagnostic purposes, to quantify liquidity in the institutional property market, and to provide a measure of “constant liquidity price movements” (in the case of the Demand Index). However, these metrics have been primarily used by academics and in basic research and to date have found only limited use in industry.

Considering the above, the author’s recommendation is that NCREIF should undertake regular quarterly production and publication of what is here labeled the “NTBI” as an official NCREIF product (though for publication this could simply continue the “TBI” label). In addition, it is the author’s suggestion that NCREIF allow occasional updates of the of the Demand and Supply indices as they have been being produced at MIT, not as official NCREIF products, but to serve special requests. It would be understood that any such production of TBI Demand and Supply index updates must be produced by parties who have the capability to run the necessary regression-based models on their own (with the necessary data supplied by NCREIF under confidentiality agreements), and explicitly without NCREIF endorsement or confirmation.

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A Simplified Transactions Based Index (TBI) for NCREIF Production

by David Geltner

1. Background

> *"In summary, we argue that the NCREIF Index is ready to evolve into two more specialized successor families of index products: one tailored for fundamental asset class research support, and the other tailored for investment performance evaluation benchmarking and performance attribution."*
> -- From: D.Geltner & D.Ling, Benchmarks & Index Needs in the U.S. Private Real Estate Investment Industry: Trying to Close the Gap (A RERI Study for the Pension Real Estate Association), October 17, 2000.

The National Association of Real Estate Investment Fiduciaries (NCREIF) is a non-profit industry association founded in 1982 to serve the institutional real estate investment community as a non-partisan collector, processor, validator and disseminator of real estate performance information. NCREIF's seminal information product is the NCREIF Property Index (NPI) which publishes quarterly investment performance results for properties held on behalf of tax-exempt institutions by NCREIF's data-contributing members, which represent the majority of all major U.S. pension fund core real estate investment holdings. The NPI has become a major reference and benchmark of U.S. real estate investment performance and is widely cited and used in both academic and industry research.

An issue which has long been raised regarding some types of research is the fact that the NPI is based on appraisals, or estimated valuations of its constituent properties as reported by the data-contributing members. The quote at the top of this page is from a 2000 white paper commissioned by PREA which suggested that, as valuable and relevant as the NPI is for many important types of analysis and research, the industry could benefit from the development of complementary index products based more directly and purely on realized transaction prices of properties sold in the marketplace.

With this in mind, the MIT Center for Real Estate proposed to NCREIF in 2004, and NCREIF supported, the development of a "transactions based index" (TBI), based on the actual transaction prices of the properties sold from the NPI database. Over the course of 2004 and 2005 the TBI was developed at MIT by a team led by David Geltner and Henry Pollakowski at MIT and Jeff Fisher at Indiana University. The TBI methodology and initial index results were presented at several academic and industry research gatherings during 2005 and 2006, and published in great detail in a 2007 article in one of the top academic real estate journals (hereinafter referred to as "FGP2007").[1] At its annual fall meeting in 2005 NCREIF approved the regular on-going quarterly production and publication of the TBI by, and at, the MIT Center for Real Estate, with the proviso that the TBI was not to be labeled or identified as an official NCREIF product. MIT launched the regular quarterly publication of the TBI in February 2006 with the 4th-quarter 2005 index results (and index history going back to 1984), and MIT has published the TBI every quarter since then (now through 4Q2010).[2]

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[1] J.Fisher, D.Geltner, & H.Pollakowski, "A Quarterly Transactions-based Index of Institutional Real Estate Investment Performance and Movements in Supply and Demand", *Journal of Real Estate Finance & Economics* (2007) 34:5-33.
[2] The TBI has been published electronically, on the **MIT**/CRE website at: *http://web.mit.edu/cre*. Note that, like NCREIF, MIT has always clearly stated that the TBI is not an "MIT product", and is not to be officially named or labeled as such. The MIT

In the five years since the start of the TBI's regular publication, the index has gradually gained an important user constituency. The TBI is frequently cited in academic articles (as of late 2010 the FGP2007 article had 39 citations in Google Scholar[3]) as well as in industry reports and white papers[4]. The Federal Reserve Board research staff employs the TBI in their quarterly update to the FOMC, and both Bloomberg and the Federal Reserve Bank of St.Louis have requested redistribution rights for the TBI.[5] Ibbotson Associates regularly provides the TBI by request to selected clients.

Purpose of the present report:

With the above in mind, NCREIF is presently contemplating taking in-house the production and publication of the TBI, as a NCREIF product. Correspondingly, MIT is looking forward to transferring much or all of the TBI production and publication responsibilities to NCREIF. The purpose of the present paper is to present some ideas and considerations to help facilitate this transition. In particular, a simplified version of the TBI will be presented and proposed.

2. What is the TBI & Why is it Useful?

As it has been produced at MIT, the TBI is a set of related indices all using the same underlying transaction price based methodology, as described in the FGP2007 article (available on the **MIT**/CRE website). The TBI is produced at the "All-property" level, which aggregates all NCREIF sold properties as if in a single population. The TBI has also been produced separately at the national sector level for each of the four core commercial property usage type sectors: apartment, industrial, office and retail, in each case based on independent separate (purely within-sector) populations. For each of these five aggregations, the TBI product suite has included four indices: Price change (or capital return), Total return (which includes income), Demand-side reservation price changes (referred to as the "Demand Index" or "constant liquidity index"), and Supply-side reservation price changes (referred to as the "Supply Index"). Thus, there are in all 20 indices (4 different indices each for the five different aggregations including the four sectors and the all-property aggregate). Like the NPI, the TBI is a quarterly index, updated at the end of each calendar quarter. The TBI has been considered preliminary during the current calendar year until the final end-of-year update after which the index has been "frozen" (not subject to any further changes).[6]

Center for Real Estate has always provided the TBI *gratis* and *pro bono* as a service to the academic and industry research communities.

[3] As another indication, this article ranks 9th out of 141 articles published in the *JREFE* from 2006 through 2008 in the number of its subsequent citations (by other articles) within the Social Science Citation Index, the premier index of academic journals in the economics and finance field. This is a good measure of the relative influence of an article in the academic community.

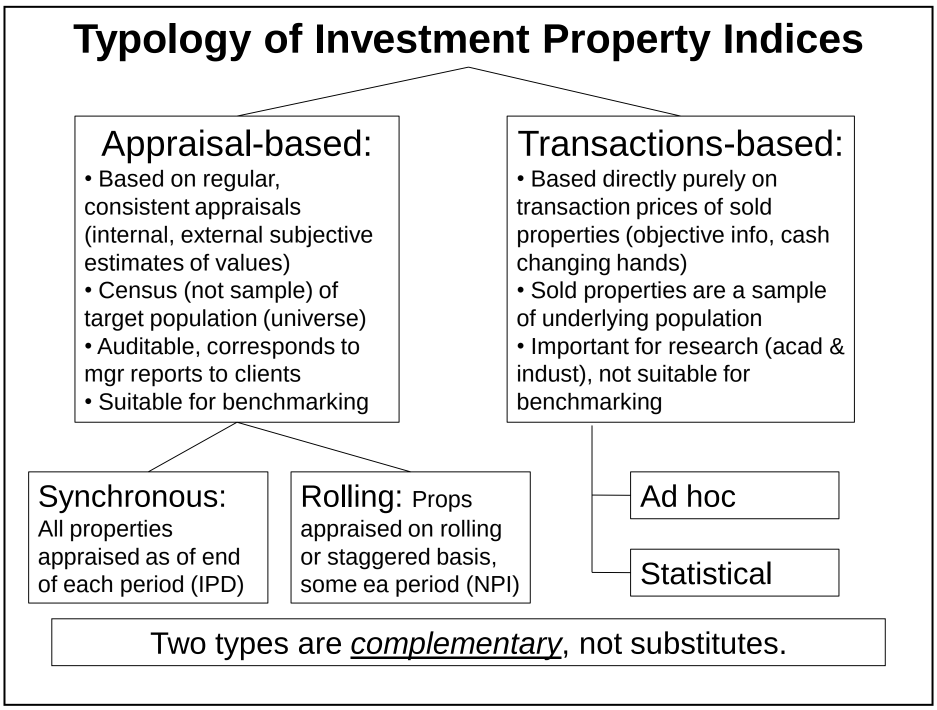
[4] A typical example is: G.MacKinnon, "REITs and Real Estate: Is There Room for Both in a Portfolio", PREA Research Report, October 2010.

[5] Rights which, through 2010, no one had authority to give.

[6] This "freezing" of the TBI is done for convenience of users, including to give index *levels* a permanency as reference benchmarks for historical price levels. It is also done for consistency with the official NPI, which is also frozen. As a practical matter, the TBI has generally not experienced significant "backward adjustments", or changes to its previously estimated history as new sales data is appended to the historical database each quarter. (The TBI is not a "repeat-sales" index, which is a type of price index construction methodology in which backward adjustments can be more of an issue.)

To better appreciate what the TBI is and how it is useful in the context of the institutional real estate investment industry that NCREIF serves, let us step back and survey broadly the types of indices that can be constructed for tracking and quantifying the pricing and investment performance of commercial properties in the U.S. As suggested in Exhibit 1, at a very broad-brush level one can distinguish two major types of investment property asset price and/or return indices: appraisal-based and transactions-based.[7]

Exhibit 1



Transactions-based & Appraisal-based Indices:

Appraisal-based indices like the NPI are the original and "classical" type of performance index in the institutional real estate investment industry. They are uniquely useful by virtue of providing a complete and auditable "census" of ***all*** of the properties in a given specifically identified population of interest (e.g., NCREIF approximates the "universe" of all core properties held by or on behalf of major tax-exempt institutions in the U.S., all the data-contributing members of NCREIF). Because of this, and because the appraisals on which such indices are based correspond closely to how net asset value and

[7] This ignores other types that are less relevant in the present context, such as REIT-based indices, and survey-based "notional" indices based on brokers' opinions. The description of "Appraisal-based" indices in Exhibit 1 has in mind in particular the rigorous, auditable investment performance benchmarking oriented indices compiled from exhaustive sets of property investment database-contributing members' valuation reports, such as that of NCREIF and the Investment Property Databank (IPD). Other types of what might be termed "expert estimation-based" indices are also possible, such as Green Street's recent "GSA-CPPI", but may differ in important ways from the traditional appraisal-based indices considered here.

investment performance is officially reported by funds and investment managers to their investors and clients, appraisal-based indices are most appropriate as benchmarks for gauging and understanding investment management performance, and for tracking at a broad level the fundamental property valuations underlying the official "book value" or "carried value" of the institutional investor clients of such investment managers.

However, appraisal-based indices tend to exhibit what researchers refer to as "smoothing" or "lag bias". By necessity and norms of practice, the property-level appraisal process that underlies appraisal-based indices tends to be more conservative about recognizing value changes, and more "backward-looking" for price discovery and documentation, than are the principal parties engaging in actual transactions. Also, in some cases the appraisals (or valuation reports) used in the index are effectively not updated for all properties as of the end of each period (i.e., the appraisals in the index are staggered or rolling in time). The overall result is that appraisal-based indices tend to exhibit dampened market cycle amplitude and/or lagged turning points in the cycle, as well as lower return volatility, compared to transactions-based indices. This smoothing and lagging bias can be problematical for certain types of investment industry research, including market tracking, trading strategies, portfolio analyses, and comparisons across major investment asset classes (such as real estate, equities, and fixed income).[8]

There are also some important populations of commercial investment properties that are not regularly appraised (e.g., the broad population of ***all*** U.S. institutional commercial property, beyond just that held by NCREIF members, including properties held by REITs and properties collateralizing CMBS). For such properties, appraisal-based indices are not possible, but transactions-based indices can and are produced.[9] Therefore, for apples-to-apples comparisons between NCREIF property performance and such broader populations, a transactions-based index for NCREIF properties is useful in principle.

Transactions-based indices, if well constructed, can address many of the above-noted issues concerning appraisal-based indices, and provide a different perspective more directly reflecting movements in the pricing within the asset marketplace. Transactions based indices thereby can provide a very useful and interesting *complement* to (but not substitute for) appraisal-based indices, in the context of NCREIF's mission. Transactions-based indices by definition are based directly and purely on actually consummated property asset sale transactions. Apart from possible reporting or recording errors, they are thus based on completely objective price information, rather than the more subjective and judgment-based valuation estimates that underlie appraisal-based indices. Methodologically, transactions-based indices are in principle completely replicable. Transactions based indices have the theoretical virtue of being based on the actual timing and amount of *cash changing hands* in the free market, thereby obeying

[8] For example, appraisal-based smoothing and lagging have the effect in classical mean-variance optimized portfolio allocation research of making the role of the private real estate asset class appear greater than it actually is in comparison with the other asset classes that do not suffer from appraisal smoothing effects, such as stocks and bonds. This undercuts the usefulness of appraisal-based real estate indices in mixed-asset investment analysis research and can undercut the credibility of real estate as a core institutional asset class. Technically, the problem is that the smoothing and lagging bias tends to reduce real estate's apparent volatility and covariance with the other asset classes.

[9] The initial example is the Moody's/REAL Commercial Property Price Index (CPPI), a repeat-sales index based on the Real Capital Analytics Inc database of property sales over $2,500,000, based on methodology developed at the MIT Center for Real Estate, produced and published monthly since December 2006. A similar more recent such index is the CoStar Commercial Repeat-Sales Index (CCRSI), produced and published monthly by CoStar Group since August 2010.

the classical dictum: *"follow the cash."*[10] Transactions prices, in contrast to appraisal-based valuations, directly reflect the current equilibrium, such as it may be, between buyers and sellers in the asset market at any given time. All of the above gives transactions-based indices a certain type of credibility and meaningfulness both among academic economists and among many practitioners and policy makers. Such credible price tracking information can be useful for the real estate investment industry, helping to raise the credibility and depth of understanding of the industry among a broader constituency. Transactions based indices are also a useful practical tool in conjunction with appraisal based indices, as the transactions based indices tend to temporally lead the appraisal indices in the major price movements or turning points. Transactions based indices therefore tend to be more predictive, and they reduce the smoothing and lagging bias problem noted previously.

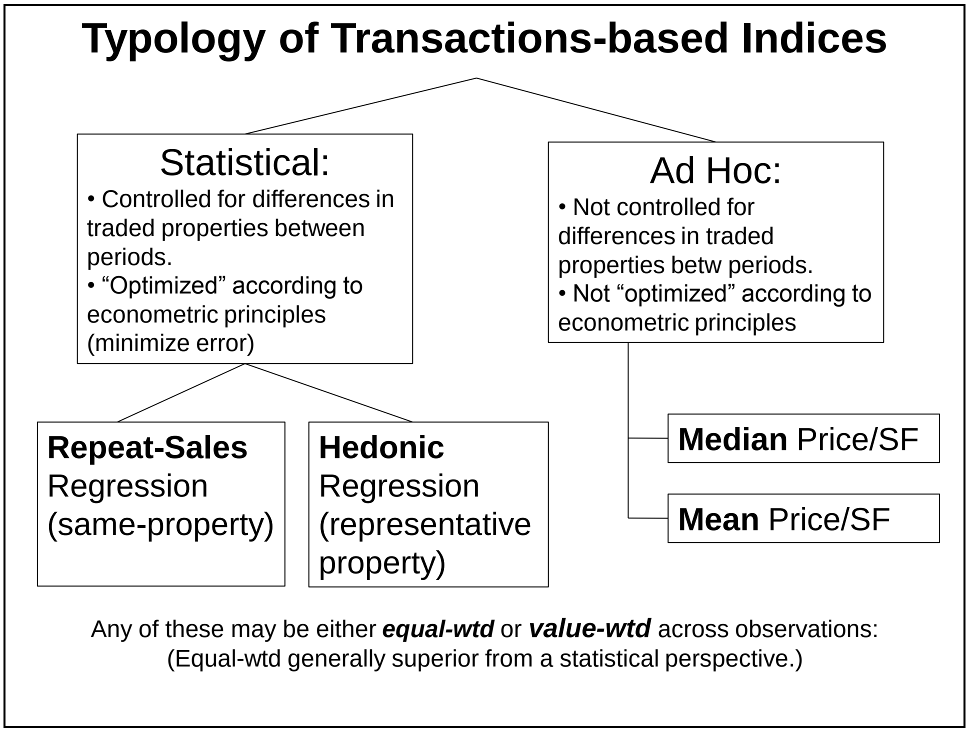
Types of Transactions-based Indices: Ad hoc vs Statistical…

With this in mind, let us continue our overview of index typology, now focusing within the world of transactions-based indices. Here one can distinguish two major approaches to transactions-based index construction, as indicated in Exhibit 2 (on the next page). *Ad hoc* price indices are based on simple average price metrics, without use of econometric optimization techniques or explicit control for differences among the properties transacting in one period compared to the next. *Ad hoc* transaction price based indices have been around for a long time in the housing industry, such as the National Association of Realtors Median Home Price Index. Similar such indices in commercial real estate tend to be more recent and not as high profile or not regularly published, but are available from sources such as Real Capital Analytics and CoStar (among others). But *ad hoc* price indices have more serious problems for commercial real estate than for housing, because of the much greater degree of heterogeneity across individual properties in the commercial market. This leads to a major apples-vs-oranges problem in comparing the average prices of properties sold one period with the average prices of properties sold the next period. If, for example, the average price per square-foot increases from one period to the next, to what extent is that due to an actual increase in same-property (or "same-store") asset prices, or rather to some sort of "flight to quality" in which a larger proportion of "premium" assets were sold during the second period? Such *ad hoc* indices also do not take advantage of the capabilities of modern statistics and computational power to minimize error or noise in the price indices.[11]

[10] Good transactions-based indices, like the TBI, strive to filter out from the index database deals that are not "arms length", whose prices do not reflect free market exchange.

[11] A major attempt to produce what would here be classified as an *ad hoc* transaction price based index of commercial property occurred in 2007 with the launch by Standard & Poor's of their S&P/GRA Commercial Real Estate Index available for trading on the CME (ticker: SPCREX). This was a type of average price per square foot index that attempted to control for differences in property types trading from one period to the next, but in an *ad hoc* manner without use of formal regression models. The index folded at the end of 2008 after it failed to register a significant decline in prices during the market collapse of that year, and with no trading of the index taking place. A more recent index which is a bit hard to classify is the Green Street Commercial Property Price Index (GSA-CPPI, launched in 2009), which is based on Green Street's value estimates of REIT-held properties (used to construct Green Street's REIT NAV estimates). As the author understands this index, though Green Street states that transactions are considered in the GSA-CPPI's computation, the GSA-CPPI attempts to represent a leading indicator of property price trends by including information gleaned from brokers and information about deals in the negotiation phase in addition to closed transactions. The exact index construction methodology is not clear, and it is not clear to what extent formal econometric models are employed. The GSA-CPPI is interesting, but seems to be clearly (and perhaps purposely) a subjective measure, at least in part, and in that sense more akin to an appraisal-based index than a pure transactions-based index, though a very different type of "appraisal" process than what underlies the NPI.

Exhibit 2



For these reasons, most academics, and more recently some of the more sophisticated industry researchers, advocate statistically rigorous, econometrically-based transactions price indices. Such indices make use of statistical regression to estimate the changes in market prices from one period to the next, with more explicit and effective controls for differences in the type and quality of properties transacting in different periods. On the other hand, *ad hoc* indices can sometimes have an advantage over statistical indices in that many industry practitioners lack familiarity or comfort with regression models of property prices. The *ad hoc* indices may appear more transparent or easy to understand without specialized expertise, in some cases.[12]

The TBI as it has been produced at MIT represents an econometrically rigorous statistical index, based on all, and only, the properties sold each quarter from the NCREIF population of properties (that is, the properties included within the NPI). As will be presented later in Section 4, this paper will propose a simplified version of the TBI that might be classified as an *ad hoc* index by the criteria described in this section. However, it will be shown that the proposed simplified methodology replicates extremely closely the econometrically based TBI that has been being produced at MIT. Indeed, the simplified TBI methodology proposed in this paper attempts to have "the best of both worlds", by taking advantage of NCREIF's unique data advantages to produce an index that essentially reflects the rigor and purity of a

[12] This is not necessarily always true, particular if one delves into the details of index production, and in any case may be a problem more of communication about index methodology than an inherent or irreducible problem of the index methodology itself. It is also the type of problem that tends to go away over time, as the industry gradually learns about the transactions based indices, which are a relatively new type of information product in commercial real estate.

statistical transactions based index while retaining the transparency and intuitive appeal of a simple *ad hoc* type index, as we shall see in the next section.

3. How does the TBI work?

In this section we will review the way the TBI has been being produced at MIT so as to facilitate the understanding of, and transition to, the simplified TBI production method being proposed in this paper.

As produced at MIT, the TBI is based on a statistical regression model of the transaction prices of the NCREIF sold properties. This is known in the academic literature as a "hedonic" price model. It will be useful to understand something about this methodology even if NCREIF will use a different methodology going forward, as the TBI to date has been based on this price model and the proposed simplified TBI in fact tracks the regression-based index extremely closely.

A hedonic price index controls for the differences between properties transacting in consecutive periods of time by the use of "hedonic variables" in a regression model of property transaction prices. The hedonic variables describe the essential price-determining characteristics of each property. In classical academic hedonic price models the explanatory variables typically include parameters such as the size, age, and location (e.g., neighborhood, or distance from CBD, or from airport, etc) of the property. The regression's estimated coefficients on the hedonic variables control for <u>*cross-sectional*</u> differences which could affect prices among the properties in the transaction sample. If the hedonic variables are all temporal constants (i.e., they don't vary across time within a given property, e.g., property size), then the price model will also include time dummy variables (i.e., set equal to one for the period when the property transacts, zero otherwise). The coefficients on these time-dummy variables will then reflect the <u>*longitudinal*</u> (i.e., *across time*) differences in prices, and it is these longitudinal differences that matter for constructing the price index.

If some of the hedonic variables also vary across time (e.g., property age, or more to the point: property's current appraised value), then the price index must be constructed by defining a "representative property" whose hedonic characteristics are used in the right-hand side of the equation. The price index is then defined by the changes in the model's predicted price for the representative property each period. To reflect "same-property" (or "same-store") asset price changes in the index such as investors actually face, it is necessary to somehow reflect in the hedonic variables the aging of the properties from one period to the next, so that the representative property reflected in the index ages one-for-one with the passage of calendar time (this of course is the case in property appraisals as they are updated for the same building over time).

A data challenge in constructing a hedonic transactions-based index is that it requires good and consistent hedonic data on all the properties in the transaction sample, for all of the important hedonic variables. This is often problematical for commercial property in the U.S. Another (related) problem is the issue of defining an appropriate "specification" of the model, that is, which hedonic variables to use, and how to use them (e.g., what functional form, for example, shall one consider building age as a linear variable in years, or a quadratic variable in years and years-squared, or what?...) These challenges often make it difficult to construct useful hedonic price indices of commercial property, particularly from a practical perspective for industry usage as opposed to purely academic study.

The TBI's Advantage as a Hedonic Price Index:

Fortunately, the NCREIF Index database provides a unique way to get around this data limitation, because the properties in the NPI are all subject to frequently updated appraisals that are generally of high quality and largely consistently made. The recent appraised value (or, more exactly, the NCREIF data-contributing member's officially reported valuation as employed in the NPI) of each property just prior to its sale can be employed as an excellent "catch-all" composite hedonic variable, for use on the right-hand-side of the hedonic price model.[13]

The recent appraisals capture almost all of the cross-sectional dispersion in the price-determining property characteristics across the properties that are sold in the NCREIF database. The recent appraisals also capture most of the longitudinal variation in property values, as the appraisals are frequently updated and do largely reflect the changes over time in the market value of the properties (as indicated in the appraisal-based official NPI capital return index). The time-dummy variables in the TBI price regression therefore don't have to do as much "work" as typical time-dummy variables in a more traditional academic hedonic price model. They don't need to capture all of the longitudinal changes in value, but rather only the relative ***difference*** between transaction prices and appraisals each period. They thus reflect, and enable "correction" of, the effect of the previously noted smoothing and lagging bias in the appraisals.

The TBI is then constructed essentially as indicated in Exhibit 3 (next page), as the percentage price changes implied by the changes in the model's predicted transaction price of the TBI's representative property each period. The representative property is constructed so that its appraised value each period (which is an explanatory variable on the right-hand-side of the price regression equation) reflects the appreciation returns in the appraisal-based NPI capital return index. The TBI's predicted price for the representative property thus reflects both the evolution of the appraised values in the NPI as well as the model's estimated time-dummy coefficients which reflect the relative differences each period between the transaction prices of the NCREIF properties sold that period versus their recent appraised values.[14]

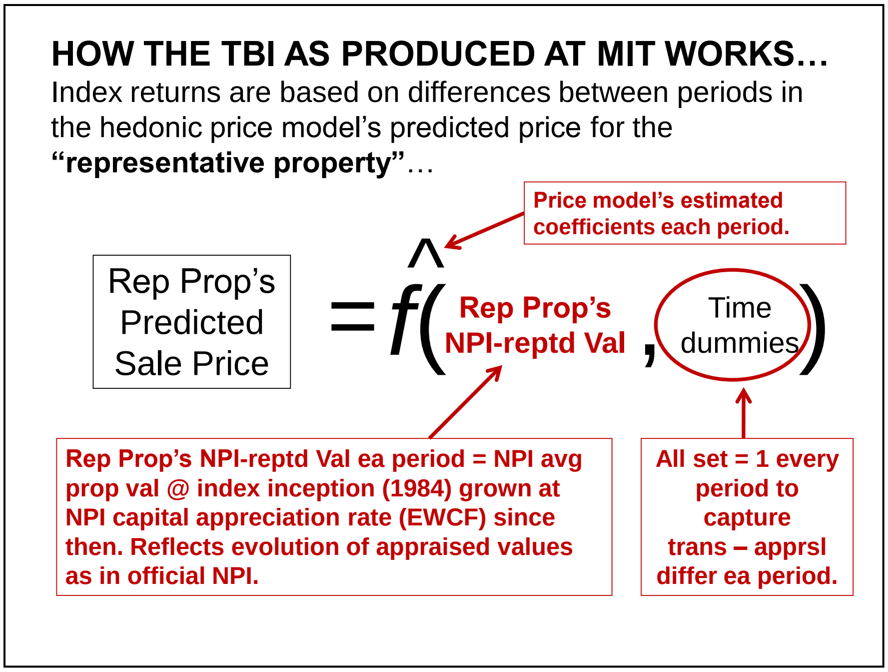
In essence, one can think of the TBI capital return each period as consisting of two additive components: (1) The change in the Representative Property's appraised value since the previous period (as reflected in the NPI capital return index); plus (2) The change in the relative *difference* between the transaction prices and the appraised values (reported two quarters earlier) between the previous period and the current period (the difference in the hedonic price model's time-dummy coefficients between the last period and the current period). For example, suppose the appraisal-based NPI capital return in Quarter "t" is 2%, and suppose in Quarter "t" transaction prices (of deals closed in Quarter "t") average 5%

[13] To be more precise, the TBI uses the NPI reported valuation two quarters prior to the sale, so as to insure independence between the appraisal and the subsequent transaction price. In many cases the data contributor knows of a forthcoming agreed transaction price, and simply reports that as the property valuation for the NPI in the current quarter of the sale transaction and often even in the prior quarter. This is a practice that is entirely proper for the NPI, but would inject a tautological element into the regression model of the price if we did not go back to an earlier valuation report. We find that two quarters prior to sale is sufficient.

[14] The previously-noted two-quarter lag is also accounted for in the index construction. That is, the representative property's "appraised value" reflects the NCREIF appreciation index two quarters earlier, as the model's time-dummy variable coefficients reflect the differences between the current transactions (closings) prices and those properties' appraised values two quarters prior.

above the “t-2” appraisals of those same sold properties. Suppose further that in Quarter “t-1” transaction prices averaged 4% above the “t-3” appraisals (for the “t-1” sold properties). Then the TBI capital return for Quarter “t” would be (in essence): 2% + (5% - 4%) = 2%+1% = 3%.[15]

Exhibit 3



4. Addressing NCREIF’s Requirements for TBI Production: A Simplified TBI…

The focus of the present paper is to assist NCREIF in making the TBI an official NCREIF information product, including NCREIF taking over responsibility for production and publication of the TBI. With this in view, an important consideration is the methodological nature of the TBI. As it has been produced at MIT, the TBI is based on an econometric model, the hedonic regression price model described above. Yet NCREIF does not wish to take on the production and publication responsibility for an index that has the level of statistical modeling involved in the pre-existing TBI, including in particular the hedonic price regression model that is at the core of the TBI as it has been produced at MIT.

This leads to the present proposal for a slightly different “TBI” based on a simplified methodology, in effect, a type of *average price* index not relying on regression analysis. In essence the simplified methodology being proposed is to compute the average each quarter of the ratio of the relative price difference between the transaction price and the recent prior appraised (NPI-reported) valuation of the sold properties each quarter, and then to apply this average ratio to the NPI capital return index level, to

[15] This is a slight simplification, as the model actually contains some other explanatory variables and other features of the statistical regression system, and as a mathematical device the MIT TBI’s regression model works in logs. But the above numerical example captures the essence of how the TBI works, and also suggests intuitively why and how a simplified version of the TBI could work, as will be described in the next section.

"convert" it to a transaction price based version. Such a procedure might be labeled as *"ad hoc"* according to the earlier discussion of transaction based index methodologies in Section 2. While it was suggested there that in general there can be problems with such methodology for commercial property price indices, we shall see in this section that a NCREIF-based average price index in the spirit of the TBI can be quite effective, essentially just as effective as the econometric based TBI that has been being published at MIT.

Why an Average-Price-Based TBI could work well for NCREIF:

The reason why a simple average-price based index can work well in the NCREIF context is fundamentally the same reason that we noted earlier as to why the TBI's hedonic price regression model is able to avoid the major data challenge that faces most commercial property hedonic price indices. This reason is NCREIF's unique database of high quality, frequently-updated, consistent appraisals of all the properties in the NCREIF population. These appraisals serve as the major right-hand-side explanatory variable in the TBI regression model of transaction prices, by capturing most of the cross-sectional and longitudinal dispersion in NCREIF property sales prices. In the TBI price regression, the appraised value variable is the dominant explanatory variable, with a coefficient very near unity and a standard error barely a percent or two (*"t-statistic"* in the 50 to 100 range or more), meaning that the vast bulk of the price dispersion among NCREIF property sales is explained reliably and directly by the appraised value.

Essentially, the only thing one has to do to create a good transaction price model of NCREIF property sales is to estimate the relative *difference* (or ratio) between the sale price and the recent appraised value among the properties selling within each period, and then multiply the average of these ratios each period times the appraisal-based NPI appreciation index level to convert it to a transactions price based index level each period (as suggested by the numerical example at the end of Section 3). In the existing TBI as it has been produced at MIT the job of estimating the average difference between transaction prices and appraised values each period is done in the hedonic price regression model by the time-dummy variables. Those estimated differences are then applied to the index's "representative property" whose appraised value evolves exactly as the appraisal-based NPI capital index, to, in effect, "convert" the NPI to the TBI.

But it is important to note that the basic statistical process that is used in the MIT TBI is what is known as "Least Squares" regression (LS for short), which means that the computer calibrates the model by picking coefficient values (on the explanatory variables, including the time-dummies) such that the sum of the squared values of the "residuals" (the differences between the model's predicted value of each sold property and the actual selling price of each sold property) is minimized. In this process, *by construction*, the sum of the (signed, not-squared) residuals becomes zero (as a mathematical by-product of the minimization of the squared residuals). This means that the model's average predicted sale price exactly equals the actual average sale price among the NCREIF sold properties. This begs the question: instead of using the regression model's prediction of the average transaction price, why not just directly use the actual average transaction price, as the basis for a "TBI"?

Thus, we may expect that we will get a very similar result to the TBI if we simply take the average sale price among the sold properties each quarter and compare that to the recent prior average appraised value of those properties, and apply that difference to the appraisal-based NPI appreciation index. In effect, we continue to define the "Representative Property" the same way the regression-based TBI does, as a property whose appraisal-based appreciation equals that of the NPI capital value index, and we then use the actual average transaction prices from one period to the next to define the changes between periods in the difference between transactions and appraisals that are necessary to convert the appraisal-based price return index to a transactions-based price return index.[16] This is summarized in Exhibit 4, labeling the simplified NCREIF-produced TBI as the "NTBI".[17]

Exhibit 4

HOW NCREIF COULD PRODUCE A TBI…

"NTBI" returns are based on NPI returns plus changes in the difference between transaction prices and appraised values among the NCREIF sold properties each quarter…

$$\boxed{\begin{array}{c}\text{NTBI Price}\\ \text{Level}\\ \text{(Qtr t)}\end{array}} = \boxed{\begin{array}{c}\text{NPI Price}\\ \text{Level}\\ \text{(Qtr t-2)}\end{array}} \times \left(\underbrace{\frac{\text{Qtr t Sale Price/SF}}{\text{Qtr t-2 apprsd value/SF}}}_{\substack{\text{Ratio averaged across}\\ \text{all sold props in ea qtr}}} \right)$$

Convert appraisal-based index to transactions-based index by multiplying by ratio of transactions/appraised values among properties sold each quarter.

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[16] This type of approach to examining the difference between transaction prices and the NCREIF Index valuations has a long history, going back through the 1990s with a series of reports on the differences between NPI reported valuations and sales prices. (See for example: J.Fisher, M.Miles, & R.B.Webb, "How Reliable Are Commercial Appraisals, Another Look", *Real Estate Finance* 16:3, 9-15, Fall 1999.) What is new is the idea of using these differences quarter by quarter to produce a regularly updated and published index of transactions based prices, and the discovery that such an index bears an extremely close resemblance to an econometrically rigorous hedonic regression based index in the form of the TBI as it has been produced at MIT. The result is a sort of "fusion" of industry and academic conceptions of a transaction price based index.

[17] The pre-existing TBI as produced at MIT actually works in log values per square foot (both for sales prices and appraised values), which are then converted into straight levels by exponentiation. For ease of communication we often speak simply in terms of "value" or "price" when we might technically mean log-price or log-value. In any case, in a non-regression average price based index construction methodology, working with geometric ratios (i.e., multiplying the price/appraisal ratio times the appraisal-based index value to convert to transaction price based value) makes little substantive difference compared to working with log-differences (i.e., adding the difference LN(price) – LN(appraisal) to LN(appraisal-based index value) to convert to a log transaction price index which is then exponentiated to a straight level index value). In practice, for simplicity and transparency sake in an industry context, the ratio method will be used in the simplified TBI index recommended for NCREIF.

Terminology Note: "MTBI" & "NTBI"…

At this point it will be useful to establish some new terminology. Henceforth in this paper, unless it is otherwise clear from the context, we will use the term "MTBI" to refer to the traditional regression-based TBI developed and produced at MIT, and the term "NTBI" to refer to the non-regression-based version based on average price relatives introduced here. If referring to issues that are in common with both versions, we may simply use the term "TBI".

5. Comparison of the MTBI & NTBI:

Exhibit 5 (on the next page) shows how well the expectation that the NTBI could produce index results very similar to the MTBI is born out at the All-property level. The red line marked by diamonds traces the NTBI over the past 10 years set to a value of 100 at the end of 2000. The blue line is the corresponding MTBI.[18] The black line is the corresponding NPI capital value index. From the evidence in Exhibit 5 it would seem that there is very little difference, indeed no economically significant difference, between the simple average price based NTBI and the more academic statistically based MTBI, at the All-property level. Exhibit 6 then compares the NTBI to the MTBI at the sector level, and here we see greater differences, which merit some discussion.

To begin, it is important to note that the primary focus of the development and publication of the TBI at MIT has been at the all-property level. The TBI at MIT was a pioneering project, the first regularly-published transactions-based price index of commercial property in the world, and as such it would inevitably be a "learn as we go" project to some extent. This has been particularly true regarding the sector indices.

The decision was made at the launch of the TBI in 2005 to produce the sector indices based only on the sold property samples ***within*** each sector. In other words, each sector TBI as produced at MIT was independent, based only on the properties sold within the subject sector. This seemed to make sense in 2005, when property transactions were plentiful. Even then, however, the scarcity of transaction observations within each sector made it necessary to employ a special technique in the price regression model at the sector level, known as a "ridge regression" noise filter. As transactions became exceptionally scarce during the great downturn of 2008-09, the sector indices based only on their within-sector sold-property samples seemed more problematical. This appears most notably in the case of the Retail Index, which is the sector with the smallest number of property sales in NCREIF. In the quarterly commentaries and FAQs-responses accompanying the MIT publication of the TBI updates, it was often noted that users should be particularly cautious in using the sector level TBI indices, which it was noted sometimes appeared inconsistent with the all-property results.

[18] For an apples-apples comparison, both of the transactions-based indices are based on the same database, NCREIF's "research" database as updated through 4Q2010. The version of the MTBI presented here is therefore "unfrozen", reflecting any backward (historical) revisions based on this latest database. It therefore differs slightly from the "official" MTBI which as noted previously has been frozen at the end of each calendar year and until recently has not been based on the "research" database. (NCREIF's "research" database differs from that on which the official NPI is based by including all revisions and additions into the history, whereas the official NPI has a frozen history.) In taking over production of the TBI, NCREIF may elect to officially retain the frozen history of the index as it has been published at MIT through 4Q2010, in which case the official NTBI history would differ slightly from what is depicted in Exhibit 5, in the same manner as noted above.

Exhibit 5

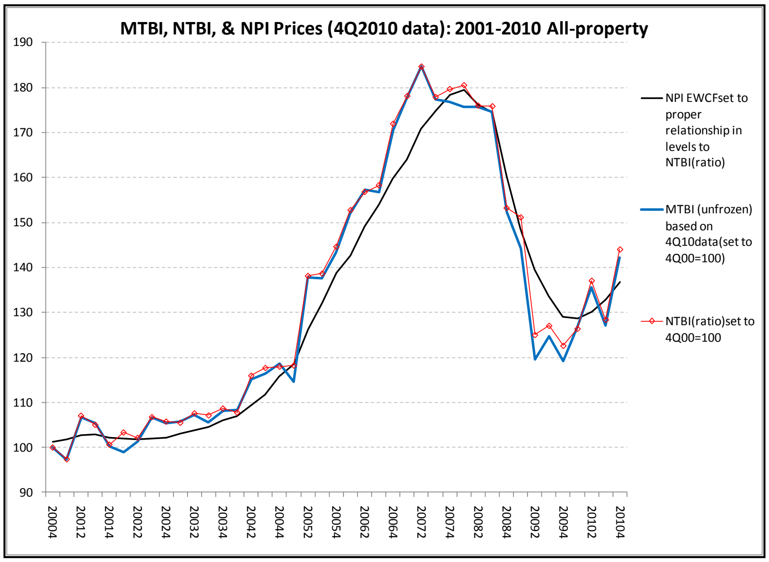
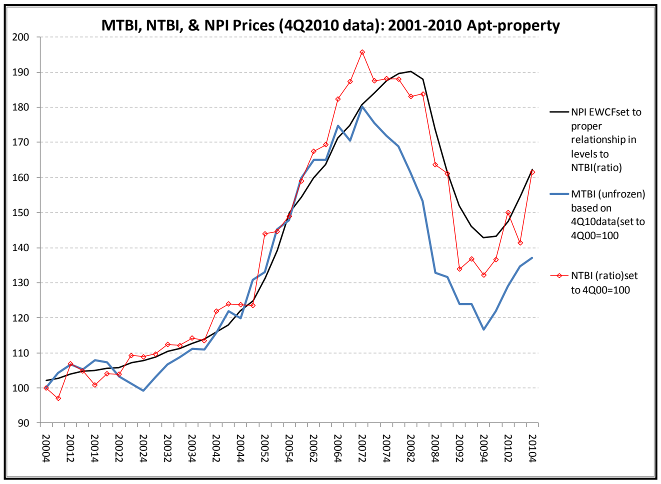
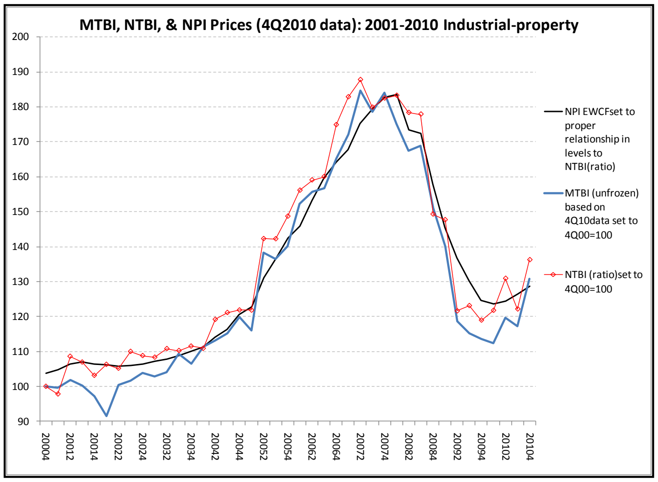
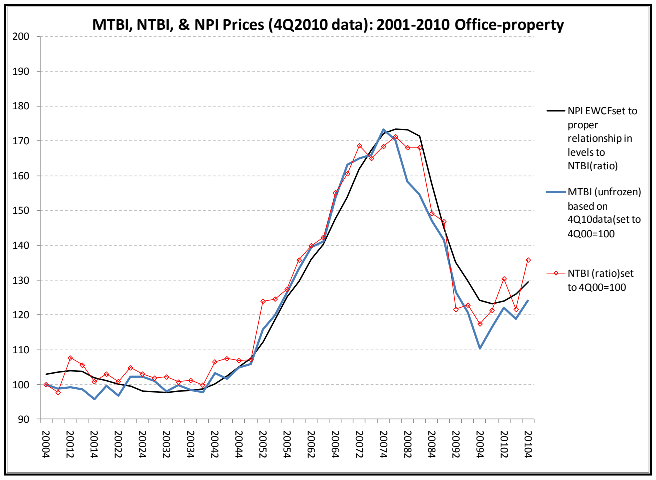
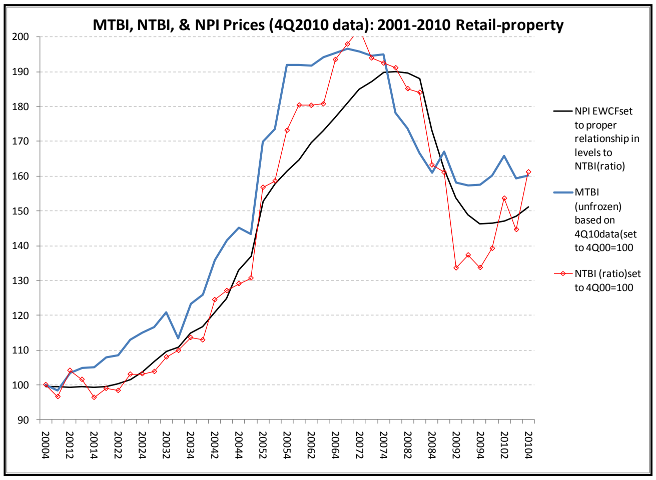


Exhibit 6: Sector Indices Comparison of MTBI, NTBI, & NPI









The transition of TBI production from MIT to NCREIF is an opportune time to revisit the methodology underlying the sector level TBI indices, and in particular to reconsider the use of the independent within-sector-only transaction samples. If we were to apply the above-described average-price-based "NTBI" procedure independently within each sector, as the MTBI has been doing with the regression-based index, we would obtain sector indices that would appear excessively noisy, even more so than the MTBI sector indices shown in Exhibit 6. [19]

Instead, we propose to base the average-price-based NTBI at the sector level on the all-property sold property sample for the purpose of computing the average transaction price/appraisal ratio. In effect, we propose basing the NTBI for sector indices or other such sub-indices on the assumption that the relative difference between appraisals and transaction prices tends not to vary systematically across the property sectors (or regions or any such breakout for which a sub-index would be produced). Under this assumption, the pooled all-property transaction price sample is as valid for estimating the price/appraisal ratio for any sector as it is for all sectors combined, and it therefore makes sense to use the largest-possible sample to estimate the price/appraisal ratio for *each* sector, namely, the all-property aggregate sample.

Thus, in the proposed NTBI represented by the red diamonds indices in Exhibit 6, we have applied the same price/appraisal ratios to each of the sectors, ratios that are based on the larger all-property sold property sample. The result is a set of NTBI sector indices that behave quite well, arguably better than the MTBI sector indices, in terms of lack of excessive noise and in terms of movements in relation to their corresponding appraisal-based NPI sector indices. The differences between the NTBI (red diamonds) and MTBI (blue) indices at the sector level in Exhibit 6 is due largely to two factors: (1) the use of the all-property transaction sample in the NTBI versus the sector-specific samples in the MTBI; and (2) the use of the special ridge regression noise filter in the MTBI sector indices.[20]

[19] The ridge regression noise filter is not possible in the simplified NTBI, and it has been that noise filter that has been largely responsible for keeping the MTBI sector indices from excessively noisy or wild-looking results. We should also note that the ridge regression noise filter was originally applied to the All-property index as well. At the all-property aggregate level the noise filter has no appreciable impact after the early years of the index, and has been dropped from the All-property index as it is currently produced at MIT. However, the early history of the All-property index would be considerably more noisy without that filter. This is one reason why NCREIF may want to retain the frozen MIT history for the All-property index. This is also why the sector indices only begin in 1994 instead of 1984 like the All-property index.

[20] There are two other sources of the difference between the MTBI and NTBI at the sector level. One is that the regression-based MTBI is estimated on a pooled sample across the entire history of NCREIF transactions, and includes some additional explanatory variables which improve the price model's fit at the individual transaction level but which are longitudinal constants and therefore have minimal impact on the index. Another source of difference is that the MTBI includes a special procedure to correct for "sample selection bias", possible systematic differences between the properties that are sold and those that remain unsold in the database. This procedure, known as the "Heckman 2-stage" procedure has generally had only a very minor effect on the MTBI results. Analysis suggests that both of these differences account for only a small part of the empirical difference between the MTBI and NTBI apparent in Exhibit 6 in the Industrial, Office, and Retail indices. In the Apartment sector these other considerations appear to play a larger role, though the NTBI apartment index still appears superior to its MTBI counterpart (at least in relation to the NPI). Finally, note that the (relatively minor) differences across sectors in the relationship between the NTBI and its corresponding NPI are due purely to differences in the NPI sector indices appreciation between their 2-quarter-lagged values (to which the common all-property based price/appraisal ratio is applied) and their current values (with any such differences appearing on a rolling basis each quarter).

Implications of the use of the all-property transaction sample at the sector level

While the assumption that transaction price/appraisal differences do not tend to vary systematically across sectors is a reasonable working assumption, which appears to yield a useful set of sector or regional sub-indices, it is of course only an approximation. It is important to keep in mind that this assumption does have the effect of causing the contemporaneous correlation across the sectors (or regions, across any breakout sub-indices) to appear larger than it otherwise would be. This is because much of the quarterly volatility in the TBI derives from quarter-to-quarter changes in the transaction price/appraisal ratio, and this ratio is being ***assumed*** to be the same across all the sectors or breakout sub-indices within any given quarter. This "excess covariance" bias should be clearly noted on any NCREIF publication of sector level NTBIs (or other breakout sub-indices), but it is not an issue with the All-property Index.

Implications of the NTBI regarding Demand & Supply indices

The simplified average price based "NTBI" methodology will allow NCREIF to produce both price index and total return index versions of the TBI.[21] However, it will not enable production of the Demand and Supply indices that have been part of the MTBI suite produced at MIT. The construction of the demand and supply indices depends on the use of regression-based econometric modeling, including a "probit" binary-choice model of property sales probability for the entire NPI population (unsold as well as sold properties), in conjunction with the previously-described hedonic price regression model of the sold properties. Of course NCREIF could certainly report simplified statistics about sales volume as a fraction of NCREIF properties held each quarter, information that obviously speaks to the level of liquidity in the NCREIF branch of the investment property marketplace. Such data about transaction volume would be an excellent complement to the NTBI price index publication each quarter. However, the econometric models are necessary to "convert" such volume-based measures into "price units" that can be applied directly to price indices.

In other words, the MTBI Demand and Supply indices have enabled analysts to make statements such as:

- *"Potential buyers reduced the prices they were willing to pay by X percent last quarter"* or:
- *"A combination of potential buyers raising their willingness-to-pay prices and potential sellers, property owners, reducing their willingness-to-accept prices, by a total of X percent as a fraction of the average current transaction price, will bring the marketplace back to its long-term average level of liquidity or trading volume."*

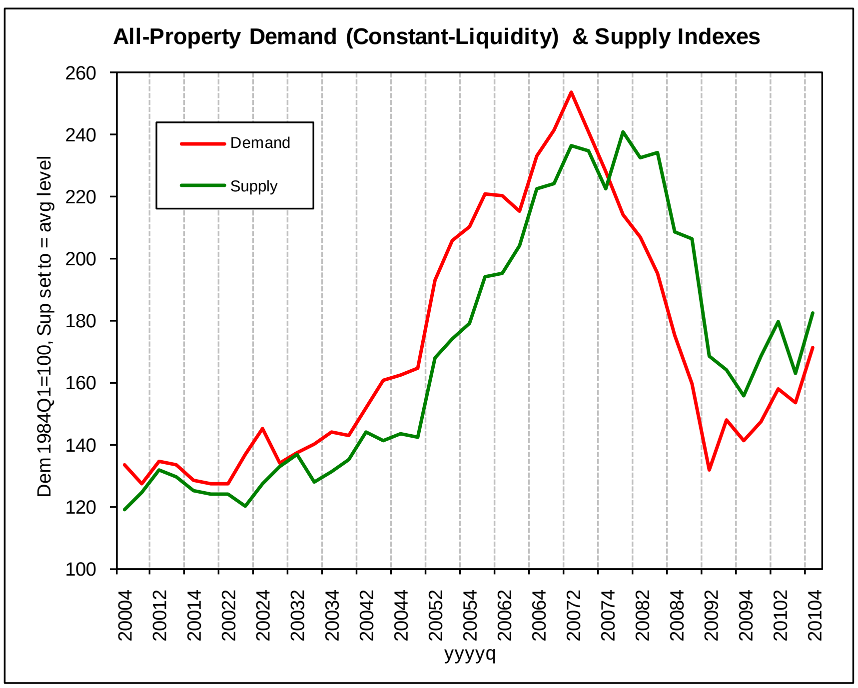
Such ***integration*** of price and volume information about the market does not occur by merely publishing volume information alongside transaction price information. The MTBI Demand Index in particular may be interpreted as a type of "constant liquidity index," tracing out the quarterly percentage changes in potential buyers' reservation prices which, if matched by sellers in actual deal prices, would keep the

[21] See Appendix B and the Excel® example templates accompanying this white paper for details of NTBI production for both the price and total return indices.

trading volume constant across the asset market pricing cycle (i.e., price movements at which property owners could sell as many properties, as quickly and easily, in a down cycle as in an up cycle).[22]

This type of information product will not be supplied by the simplified non-regression-based NTBI indices described above. While it is true that this information has not been nearly as widely used as the basic MTBI price index, there have been some users of the MTBI Demand and/or Supply indices, in both academia and industry.[23] As seen in Exhibit 7, the MTBI Demand Index was particularly effective in the early stages of the market downturn in 2007 and 2008 at indicating the extent of the drop in commercial property valuation sentiment among potential investors (witness the precipitous fall in the red, demand side, index from mid-2007 through mid-2009). At the same time, the Supply Index reveals that it was property owners' refusal to agree with that market sentiment that prevented the prices in consummated transactions from falling as far or as fast as they otherwise would have, and that underlay the drastic dry-up in liquidity in the market. The gap between demand and supply peaked at some 26 percent of the average then-prevailing transaction price in the first quarter of 2009, greater than it had been at the worst of the previous downturn in the first quarter of 1992. The chart also shows how the demand side of the market (potential investors) has been much more bullish about revising their valuations upward since the second quarter of 2009 (through 4Q2010 the demand index was up 30% from its 2Q2009 bottom, while consummated transaction prices as measured by the MTBI price index were only up 19% from their 4Q2009 bottom).[24]

Exhibit 7



[22] This perspective on the Demand Index was developed in depth in a highly cited academic paper that was the original basis for the development of the TBI at MIT: J.Fisher, D.Gatzlaff, D.Geltner, & D.Haurin, "Controlling for the Impact of Variable Liquidity in Real Estate Price Indices", *Real Estate Economics* 31:2, 269-303, 2003.

[23] The original industry user of the Demand Index, as a "constant liquidity index", was Ibbotson Associates, which still supplies this index by request to certain clients.

[24] In general, the MTBI demand and supply indices have shown that demand movements often tend to lead supply movements, that property owners' willingness-to-accept prices tend to move more conservatively than potential buyers' willingness to pay prices.

This type of perspective provides a unique real-time window into the functioning of the institutional property market, with more depth than simple transaction prices alone, by drilling beneath those prices into the two sides of the market that underlie the deals. This can be useful for diagnostic as well as basic research purposes. It would seem sad to totally and forever remove from the information marketplace the ability to access updates of these TBI Demand and Supply indices. For this reason, NCREIF may want to remain receptive to future requests on the part of parties who have the capability to produce such regression-based indices on their own, under suitable confidentiality restrictions and without NCREIF assuming any responsibility for, or endorsement of, the product.

6. Conclusions & Recommendations Regarding the NTBI & MTBI

Based on the discussion and analysis presented in this paper, it seems eminently feasible for NCREIF to take on production and publication of a "TBI" as an official NCREIF product and as a legacy of the existing "MTBI" that has been being produced and published at the MIT Center for Real Estate. This transition affords a good opportunity to make some changes in the TBI production methodology, and this paper has presented and proposed such a change, in particular, a simpler, average price based version of the TBI that does not require regression modeling. With this in mind, the following specific recommendations are made.

1. NCREIF should move to adopt regular quarterly production and publication of a transactions based index based on the simplified average price based methodology described in this white paper (labeled herein as the "NTBI", but for NCREIF publication purposes the acronym could continue as simply the "TBI" that has gained fluency in the existing user community, i.e., without the "N").

2. Sector level (or other such breakout) sub-indices of the NCREIF-produced TBI should be based on the all-property average transaction price/appraisal ratio, applied in common to each breakout sub-index, rather than being based on pure within-sector samples as the MTBI sector indices have been. This recommendation is based on the plausible assumption that transaction/appraisal ratios do not tend to differ systematically across sectors, and on the observation that using the larger all-property sample for the sector indices seems to result in better sector-level TBIs.

3. Publication of any such TBI breakout sub-indices based on the all-property average price/appraisal ratio should be accompanied by a "caveat" statement to the effect that cross-correlations among breakout sub-indices may appear larger than they otherwise would as a result of the all-property computation of the average price/appraisal differences.

4. It is recommended that in the interest of smooth transition NCREIF adopt the pre-existing frozen history of the TBI as published at MIT through 4Q2010 in the case of the All-property aggregate indices (both price and total return). However, due to the small-sample issues with the sector indices as published at MIT, and in view of the more substantial change in the sector indices reflecting recommendation (2) above, the NTBI sector indices should commence with new re-stated histories going back to their (same) inception dates of 1Q1994; and finally…

5. Regarding the Demand and Supply indices, NCREIF should continue to be receptive (as it has been to the MIT Center for Real Estate) to parties appropriately requesting to, on their own, run the Demand and Supply indices as these have been being produced at the MIT Center for Real Estate as part of the TBI up until now, under suitable confidentiality restrictions, and under the proviso that such Demand and Supply indices are not a “NCREIF product” and are not supported or endorsed by NCREIF. Also, NCREIF should consider publishing transaction volume data alongside the regular quarterly publication of the NTBI, including each quarter’s fraction of the NCREIF stock sold that quarter (by count and by dollar volume). Such volume information is a vital complement to pricing information to provide a current picture of the market.

Appendix A:

Value-weighted &/or NOI-based Versions of the NTBI

In defining the TBI representative property's appraised value in constructing the price index, the MTBI employs the equal-weighted/cash-flow based (EWCF) version of the NPI capital return index, rather than NCREIF's official value-weighted/NOI-based version (VWNOI) which is represented by the NPI. There are two considerations underlying why the MTBI employs the EWCF version of the NPI. One consideration is related to the "EW" (equal-weighted) issue, and the other is related to the "CF" (cash-flow-based) issue. In both cases, this is a discretionary or "policy" decision of the MTBI, and NCREIF could in principle elect to produce and publish an alternative VWNOI-based version as the NTBI without violating any fundamental statistical principles. This Appendix will review this policy question, and compare VWNOI-based and EWCF-based versions of the NTBI at the All-property level.

Equal-weighted vs Value-weighted indices:

The MTBI has been using the EW version of the NPI to define the index's representative property because we view the TBI as a statistical inference device rather than a "universe" or benchmark. In general statistical inference is more accurate when each observation is treated equally.

One way to see this is to think of the principle of diversification of a portfolio. To take an extreme example (which is correct for demonstrating the relevant point), a portfolio consisting of 100 nearly equal-sized assets will be more diversified (hence, have lower volatility) than a portfolio containing 99 tiny assets and one gigantic asset whose value dominates the portfolio.[25] This is why the equal-weighted version of the NPI tends to have lower volatility than the official value-weighted version.

In the TBI's original conception, before any other transactions based price indices of U.S. commercial property existed (such as the Moody's/REAL and CoStar indices today), we viewed the TBI as representing the entire institutional U.S. investment property market, a larger population than the NCREIF database. We were in effect viewing the NCREIF properties, and the sold sample from them, as representing this broader population of properties. Treating the TBI as representing a population broader than NCREIF meant treating NCREIF as a statistical "sample" of this broader population, which in turn meant that one should use an equal-weighted version of the NPI to represent the appraised value of the "representative property" used in constructing the TBI.

This perspective changes a bit if one views the underlying population of properties represented by the TBI as being not the broad U.S. institutional investment real estate market as a whole, but just the specific properties held by NCREIF members and included in the NPI. Of course, the TBI is still from this perspective a statistical inference, as most NCREIF properties are not sold each period, and thus the sold properties represent a sample of the overall NCREIF property population. Therefore the hedonic price regression model (or average price/appraisal ratio

[25] This assumes the assets all have equal individual variance and pair-wise covariance.

estimate in the case of the NTBI) should still be based on equal-weighted data-points as before.[26] But the NCREIF properties are now from this perspective no longer a sample but rather constitute the entire population of interest. From this perspective it would be valid in principle to apply the TBI's estimate of transaction price/appraisal ratios to a representative property defined (in terms of its appraised value) based on a value-weighted version of the appraisal-based NCREIF Index.

Cash-flow based vs NOI-based capital return indices:

We now turn to the question of whether to base the TBI representative property's appraised value evolution on the "CF" or "NOI" definition of the capital return (aka "appreciation return"). As is well known, investment periodic total returns (aka "simple holding period returns" – HPRs), include two components: (1) the change in the asset (or static portfolio) value from beginning to end of the period (calendar quarter in the case of the TBI); and (2) the net income or cash flow generated by the asset (portfolio) for its investors during the period. The former component is referred to as the "capital return" (or sometimes as the "appreciation return", or the "capital gain" or "growth component"). The latter component is referred to as the "income return" (or sometimes the income or cash "yield", or "current return"). The two components should be defined in a non-overlapping manner so that their sum equals the "total return" (sometimes referred to as "total yield", or simply, the "yield").

In the official NPI the capital return is defined for each property (and then aggregated up into the index) as the change in the reported valuation of the property between the beginning and end of the period *minus any capital expenditures* made on the property during the period. The official NPI capital return thus reflects *only* the effect of the market for the asset (changes in its market value) as well as the aging or "wasting" of the structure part of the asset, without reflecting how the asset's value may have been improved by capital expenditure investments made by the owner into the property. Correspondingly, the official NPI income return is defined to equal the net operating income (NOI) of the property *without subtracting capital expenditures* paid by the property owner during the period. In other words, capex is *not* subtracted from the income return even though it reduces the net cash paid out from the property to investors, and capex *is* subtracted from the capital return causing that return to represent something *less than* the change in property asset value from beginning to end of the period.

There is no doubt some rationale for this convention, and it is indeed common in many real estate indices (e.g., IPD uses a similar convention). But the NPI properties exclude development projects and major redevelopment or rehabilitation projects; so the vast majority of all the capital expenditures in question are routine in the operation of the properties, and generally self-

[26] A relevant limitation is the assumption, implicit in statistical inference, that the estimation sample is drawn from a single underlying population, as far as the parameters of interest are concerned. This can make the TBI non-representative for some segments of the property market if there arise market segments (possibly temporary) across which the relationship between transaction prices and appraisals differs sharply. For example, if larger properties systematically have a different transaction price/appraisal relationship than smaller properties. However, the solution to any such problem is probably not to value-weight the underlying data-points in the price/appraisal ratio estimation (given the small sold property sample size in any given period this would probably inject too much noise into the index). Rather, one would like to break the index into separate sub-indices corresponding to the different market segments, although again the small sold sample size might make this impractical.

financed from the operating revenues of the properties. As a result, the official NPI convention in defining the breakout between capital and income returns can be somewhat "apples-vs-oranges" and potentially misleading when comparing the NPI with stock and bond market based indices (including REIT indices). In the stock market, for example, price or capital gain indices do not subtract out the corporate capital expenditures made from earnings plowed back into the company, and income returns are defined based on dividends, the cash actually paid out to investors net of retained earnings held back in the company.

One of the major original motivations in developing the MTBI was to help provide the real estate investment industry with a historical returns series that would facilitate apples-to-apples comparisons between real estate and other asset classes (especially stocks and bonds). Therefore, the policy decision was made a the inception of the MTBI to define its representative property's appraised value evolution based on the *cash-flow* based definition of the NPI capital return rather than the official NOI-based definition. Another reason for this policy has to do with the other transactions based price indices of commercial property which have been launched since the TBI. Both the Moody's/REAL CPPI and the CoStar CCRSI are repeat-sales indices which (like the Case-Shiller and OFHEO repeat-sales housing price indices) do not subtract capex from the price-changes tracked by those indices. Thus, for apples-to-apples comparison with the other transactions based commercial property price indices, the TBI also needs to be based on the CF-based definition of the NPI capital return. This makes the TBI a true *price change* index, reflecting the changes in the average transaction price fetched by NCREIF sold properties from one period to the next (on a "same-property" basis).

Summary:

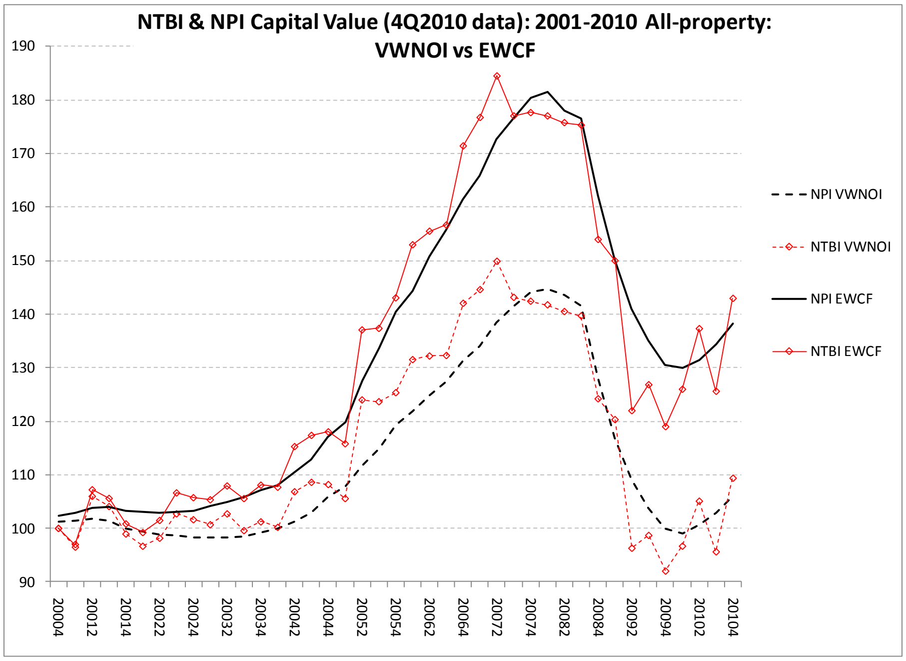
In summary, the MTBI has by policy been based on the EWCF version of the NPI capital return index. There are good reasons for this, in both the EW and CF considerations. However, particularly given that there are now other commercial property transactions price based indices, this is a policy decision that NCREIF might choose to revisit, if and to the extent that NCREIF will launch its own "NTBI" version of the TBI. From a statistical perspective, it would be possible to produce a VWNOI-based version of the NTBI, simply by applying the average price/appraisal differences to the official VWNOI-based NPI capital return index rather than to the EWCF-based version.[27]

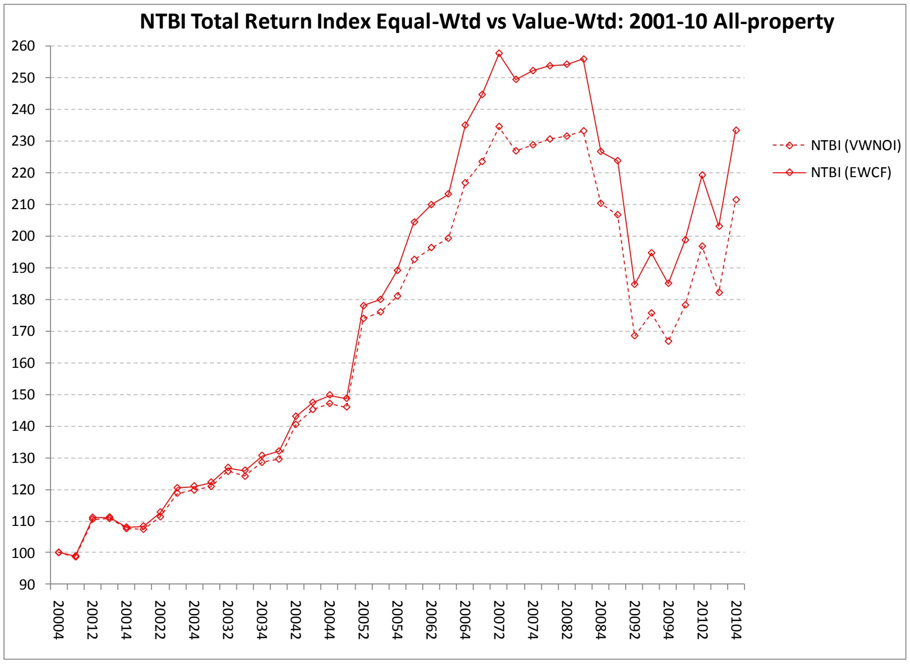
Exhibit 8 (on the following page) provides a comparison of these two alternative approaches. The top chart displays the NTBI capital value or price indices, together with their corresponding versions of the NPI. The VWNOI-based versions, reflecting the official NPI capital growth index in the NTBI's representative property's appraised value, show a markedly lower capital value growth trend, due to the effect of subtracting capex out of the capital return component. The bottom chart compares the equal-weighted vs value-weighed versions of the NTBI in the cumulative total return indices. The equal-weighted index shows a slightly higher trend,

[27] The Excel template provided with this white paper demonstrates exactly how to do this. Slight differences between the indices shown in Exhibit 8 and those in the Excel template reflect the fact that the indices in Exhibit 8 are based on log differences while the Excel template reflects ratio-based NTBIs.

indicating that on average in recent years smaller (lower-valued) properties held by NCREIF members tend to have performed better than larger properties.[28]

Exhibit 8





[28] It should also be noted that the VW index is based on the official NPI and therefore based on NCREIF's "NPI" dataset of historical property returns, whereas the EW index is based on NCREIF's "Research" dataset. The latter may have more backward-adjustments than the former, and this could also partially explain the difference between the two indices. Most of the differential trend in the total return indices is attributable to a few particular historical quarters: 2005Q4, 2006Q1, & 2006Q4.

Appendix B:
Steps in the Operational Production of the NTBI

See accompanying Excel example template

The primary rationale for the development of the simplified non-regression-based "NTBI" version of the TBI is to facilitate NCREIF in-house production of the index. A related rationale is to facilitate communication to and with the industry and practitioner community about the NTBI, including the meaning and construction of the NTBI. In fact, the NTBI has been designed to be able to be easily produced by NCREIF using only the existing NCREIF property database and Excel®.

An illustrative example of all of the steps in the production of the NTBI is contained in the Excel workbook files that accompany the transmission of this report by the author to NCREIF. The Excel workbooks start from the property-level NCREIF database and walk the reader through all the steps of NTBI construction, including both capital (price) index and total return index, with examples of both the All-property index and all four of the sector indices. The example computations reflect the EWCF-based NTBI, but the All-property template also includes an example of a VWNOI-based version. The Excel examples are fully annotated and documented, and can serve as templates for actual NCREIF NTBI production. They are based on the actual real world historical case of the 4Q2010 quarterly return computation and index update.[29]

Although the Excel example file is rather complete and self-explanatory, the essential production steps will also be explicated here.

Computation of the NTBI price index:

There are two major phases in the NTBI price index construction: property level computations, and index construction. We can divide the overall process into four major steps, which correspond to the first four tabs in the example Excel workbooks (after the "readme" introductory tab).

Step 1) Current Quarter Sold Property Compilation:
In this step the analyst compiles all of the properties that sold from the NPI database in the current quarter (which we shall refer to generally as Quarter "t"). For conformity with the MTBI, computations are based on values per square foot, and only on the core property types of: apartment, industrial, office, and retail. Thus, we drop any observations that do not have a valid square-foot entry or that are not among the four core property types.[30] We also need to base the

[29] In the case of the All-property NTBI, if NCREIF decides to retain the frozen MIT TBI history through 4Q2010, then the example in the template would be illustrative only, as the actual 4Q2010 result would be taken from the MTBI. This possibility is documented and treated in the template, which clarifies how the NTBI updating process would proceed from 1Q2011 onward.

[30] This treatment of the square-foot variable could be re-examined by NCREIF. The division by square foot was originally adopted because it was contemplated to report the price model's predictions in dollars per square foot rather than simply in an index of longitudinal percentage changes, and it was felt that price/SF would be more

appraisal value on the NPI reported valuation two quarters prior to the sale, so we must drop any properties sold in Quarter t that don't have valid square-foot and appraised (reported) valuations in Quarter t-2.[31] For the remaining valid, usable current-quarter sold property observations (which is usually the vast majority of all the property sales out of the NPI in the current quarter), you need to compile the sale price and the square-footage of each sold property.

Step 2) Lagged Two Quarters Data Compilation for Current Sold Properties:
In this step the analyst compiles the appraised (reported) valuation and the square-footage as of Quarter t-2 for all of the properties sold in Quarter t. Generally this information would be derived from the most recently updated historical dataset, the Quarter-t historical dataset, even though we are pulling information about the properties as of two quarters earlier.

At this point it is important to verify that the valuation and square-footage information for Quarter t-2 for all of the Quarter-t sold properties is consistent with the sale price and square footage information for those properties as of Quarter t. For example, if a property had a partial sale in Quarter t-2, and then the remainder of the property was sold in Quarter t, it might be necessary to drop that observation from the index estimation dataset. The reason is that the property as of Quarter t-2 before the partial sale may have been heterogeneous in terms of its value per square foot. For example, the property might have included a retail component and an office component, each with very different valuations per square foot. Supposing the retail component was sold subsequent to Quarter t-2 but before the current quarter, the lagged valuation per square foot would not be comparable to the current sale price per square foot.

Step 3) Computation of the Price/Appraisal Ratio for Quarter t:
The essence of the NTBI is to adjust the appraisal-based NPI by the average ratio each quarter of the sold properties' transaction prices divided by their recent (2-quarters prior) appraised (NPI-reported) valuations (in each case adjusted by square-footage in the present model). Thus, we compute the following ratio, which we'll label "PriceOverAppr(i,t) for Property "i" sold in Quarter-t. For each i = 1,2,…,N(t) of the Quarter-t sold properties:

$$\text{PriceOverAppr}(i,t) = (\text{SalePrice}(i,t)/\text{SF}(i,t)) \ / \ (\text{ApprVal}(i,t\text{-}2)/\text{SF}(i,t\text{-}2))$$

We then take the (unweighted) arithmetic average PriceOverAppr(t) across the N(t) properties sold in Quarter-t:[32]

$$\text{PriceOverAppr}(t) = \text{AVERAGE}_i[\text{PriceOverAppr}(i,t)]$$

---

intuitive and transparent than average price per sold property. However, this potential feature of the TBI was never implemented.

[31] See explanation for this in footnotes in Section 3 of the main body of this paper.

[32] If one wanted to construct a value-weighted estimate of the price/appraisal difference, you would first pool across all the sales within the quarter the sales prices and prior appraised values and square footage, and then perform the division and take logs on this pooled aggregate. As noted in Appendix A, this procedure risks any given quarter being overly dominated by one or a few large individual property sales, and this could add noise into the resulting TBI. It is also not necessary for deriving a "value weighted" TBI in the sense of using NCREIF's population-based value-weighted NPI as the "representative property" to which the price/appraisal differences are applied to derive the TBI (as described in Appendix A).

Step 4) Construction of the NTBI Price Index for Quarter t:
We next want to use the PriceOverAppr(t) value we have just computed to "convert" the NPI cumulative capital return index into the NTBI. We do this by first downloading the NPI capital value index (levels) from the NCREIF database, and setting this index to have a value of unity (or 100) in 1984Q1, the base period of the TBI.[33] Include in the series all the accumulated capital value levels starting two quarters prior to the TBI base period, so you will have a complete quarterly history of the NPI capital values from 1983Q3 through the current quarter indexed to 1.00 (or 100) in 1984Q1.

We then multiply each of the quarterly value levels of the NPI capital index times the price/appraisal ratio we just compute for the quarter two periods subsequent, for each quarter t = 1983Q3…current Quarter-t (or from 1993Q3 for the sector indices). This step is represented as follows:

$$\text{NTBI}(t) = \text{NPI}(t\text{-}2)^{*}\text{PriceOverAppr}(t)$$

In fact, the entire history of the NPI and TBI up until just prior to the current Quarter-t will already have been computed and recorded the previous quarter (and initially MIT will transmit this history to NCREIF), so the only change or updating that will be going on in this step is the adding on the new current Quarter-t value.

The result is an NTBI capital value index that is indexed to an inception value of unity (1.00, or 100) as of 1984Q1 (or 1994Q1 for the sector indices). You can then compute the implied price-change returns in the usual manner, for each Quarter "t":

$$g_{\text{NTBI},t} = \text{NTBI}(t) / \text{NTBI}(t\text{-}1) - 1$$

Note that Step 4 can be applied either to the EWCF version of the NPI capital value index or the VWNOI version, in exactly the same manner, depending on whether one wants the NTBI to be based on the EWCF definition of capital (price change) returns or the VWNOI definition, as discussed in Appendix A.

Computation of the total return index:

The above procedure describes how to construct the NTBI price index or capital value index. The construction of the corresponding total return index is very similar, only with an extra step to include the cash flow (or net operating income) component into the return, as demonstrated in the previously-described Excel example file (see the worksheets in which the total return index is computed). In brief, the procedure is as follows.

First, go back to the place in *Step 4* where you had the NPI cumulative capital value index set to a starting value of 1.00 (or 100) in 1984Q1. Think of these values as the value, in (say) hundreds of dollars per square foot, of the NTBI's "Representative Property" each period since 1984Q1. Now fill in a new column with the corresponding income (cash flow or NOI, depending on

[33] For the sector indices the base period is 1994Q1.

which form of NPI capital index you are using) in dollars per square foot, by multiplying the previous quarter's cumulative capital value level from the NPI (Representative Property value/SF) times the NPI *income* return (either cash flow or NOI based) for the current quarter. This computation may be expressed as follows:

$$CF_{NTBI,t} = NPI(t\text{-}1)*y_{NPI,t}$$

where "$y_{NPI,t}$" is the NPI's income return for Quarter t.[34]

Next, compute the NTBI total return in each Quarter t in the usual fashion employing the NTBI capital value levels computed previously and the cash flow (or income) values derived just above:[35]

$$1 + r_{NTBI,t} = (NTBI(t) + CF_{NTBI,t}\ ) / NTBI(t\text{-}1)$$

Finally, set the NTBI total return index to an inception value of 100 (or whatever value you want) in 1984Q1, and grow it cumulatively forward by chain-linking in the usual manner:

$$NTBI\_Total(t) = NTBI\_Total(t\text{-}1) * (1 + r_{NTBI,t}\ ).$$

[34] We don't need to "correct" cash flow or income information for transaction/appraisal differences, because presumably the cash flow and income information in the NPI is accurate and objective, not subject to appraisal or reporting effects.
[35] We don't need to explicitly employ the time-weighted denominator in this step because the NPI indices that underlie this computation already reflect such time-weighting.