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

by

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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):

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

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:

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

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:

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

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: $\hat{\omega} = \omega/\hat{\sigma} = \left(\hat{\alpha}^b - \hat{\alpha}^s\right)/\hat{\sigma}$, and $\hat{\gamma}_t = \gamma_t/\hat{\sigma} = \left(\hat{\beta}_t^b - \hat{\beta}_t^s\right)/\hat{\sigma}$.

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]

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

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:

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

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]

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

and the income return is:

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

and the total return is:

$$r_{pt} = g_{pt} + y_{pt} \qquad (13)$$

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:

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

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:

[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

[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):

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

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]

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[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

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:

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

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 1^{st}-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.

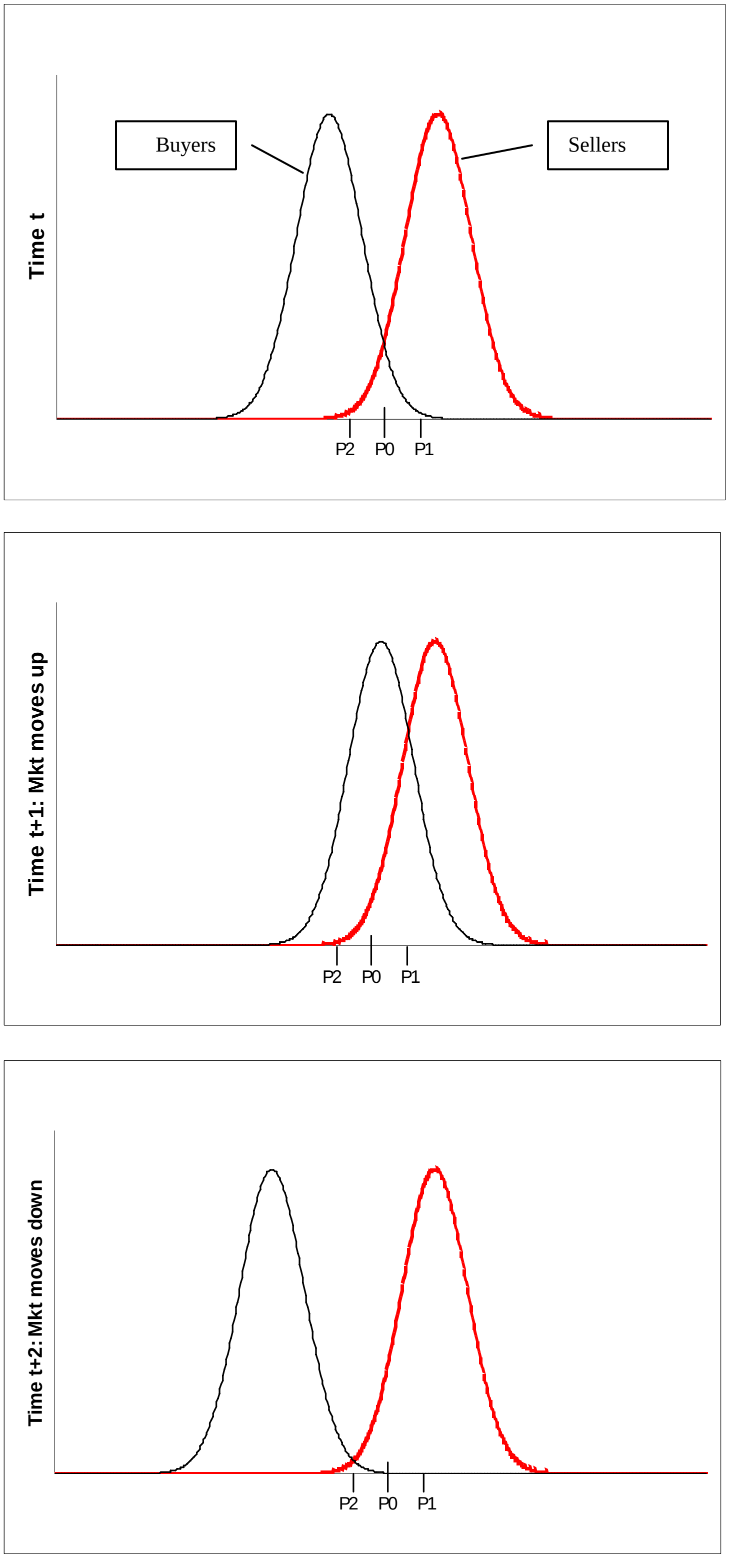


Exhibit 2: Quarterly All-property Probit Time-Dummy Coefficients (relative to average), Tracing Relative Frequency of Property Sales Transactions in the NCREIF Database

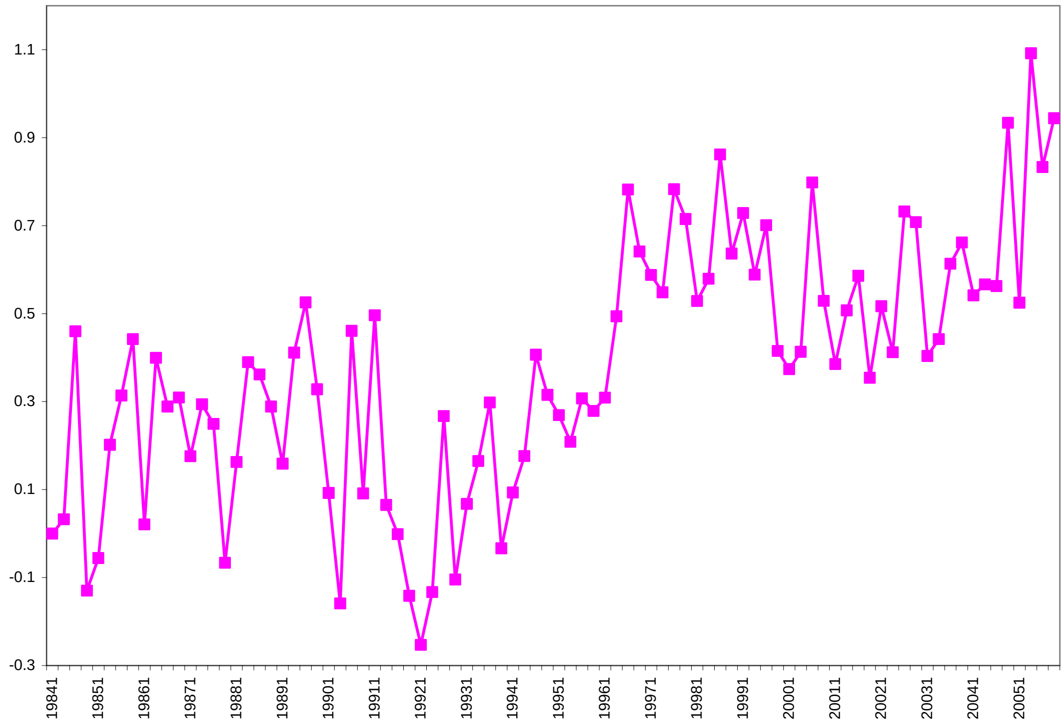


Exhibit 3: Semi-Annual Averaged Probit Time-Dummy Coefficients Superimposed on NCREIF Transaction Price Log Levels

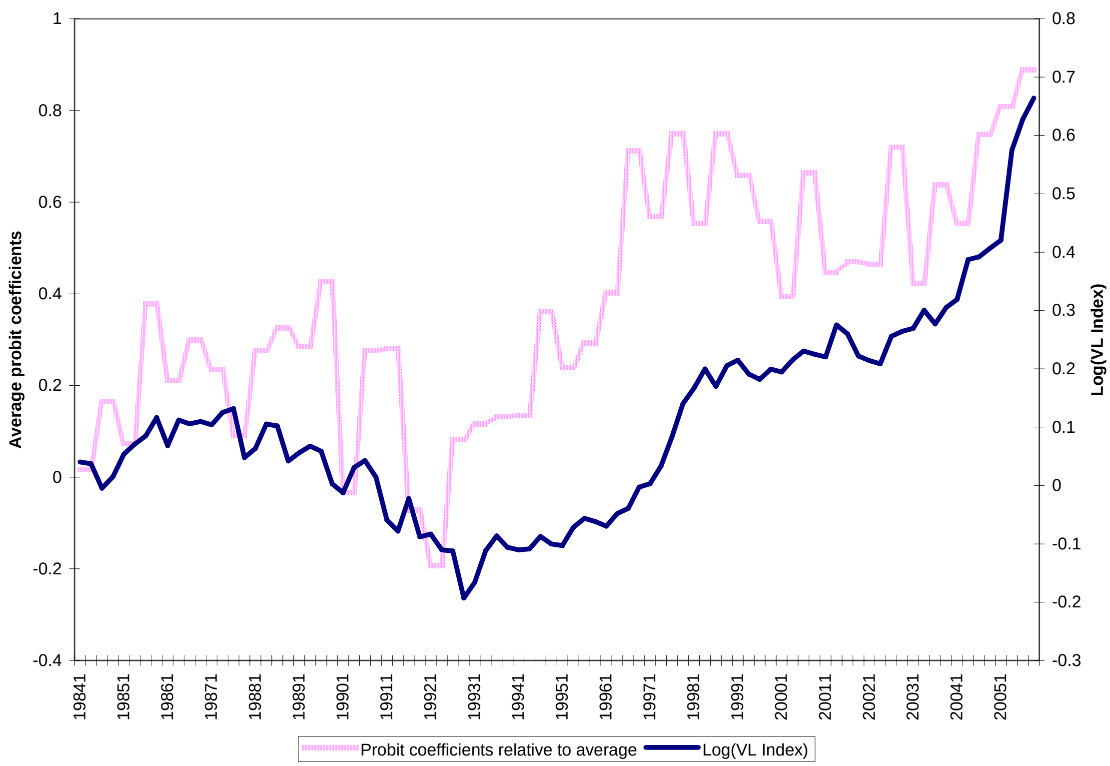


Exhibit 4: Quarterly Appreciation Levels, TBI vs NPI:

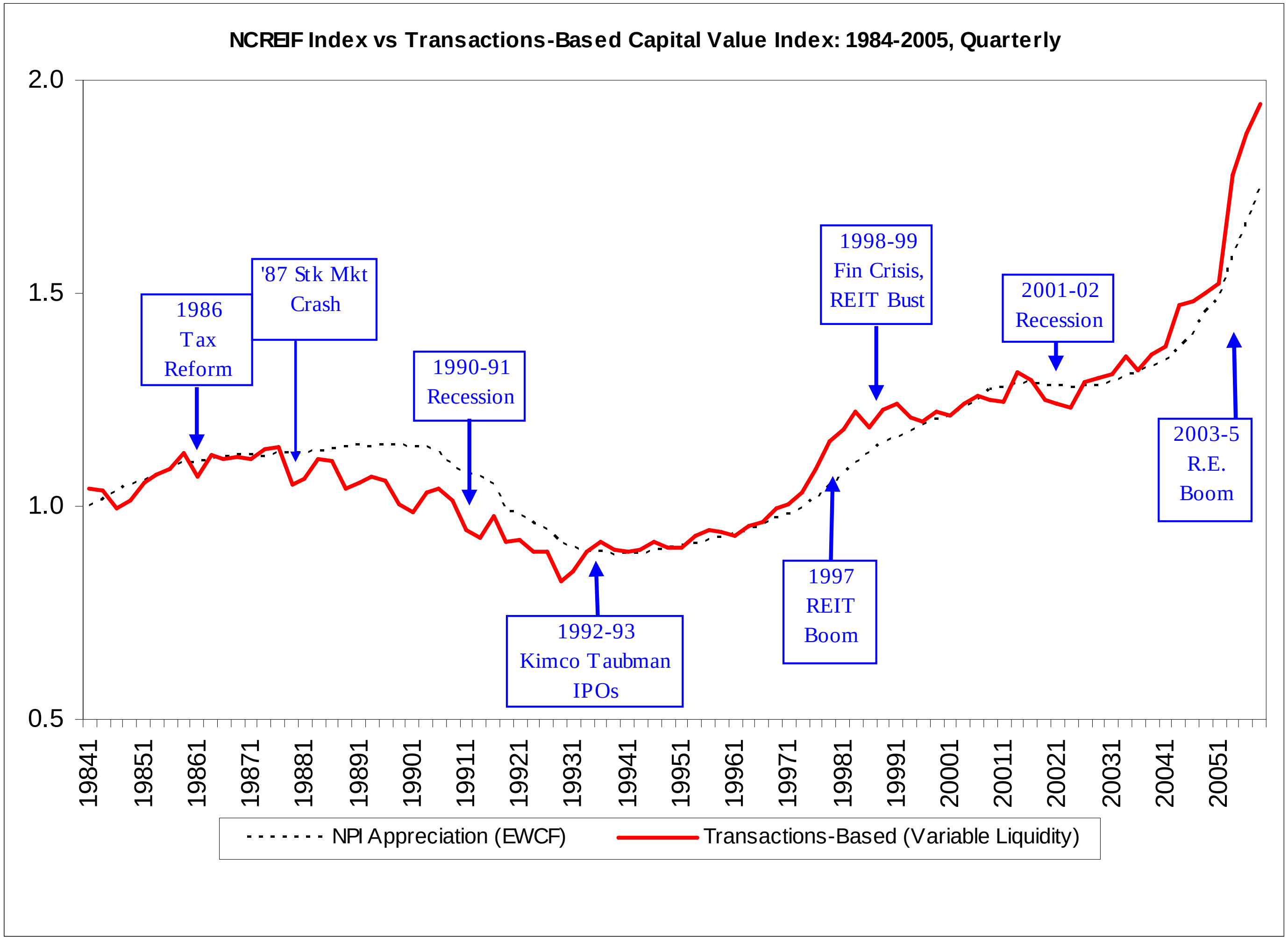


Exhibit 5: Supply and Demand Indexes

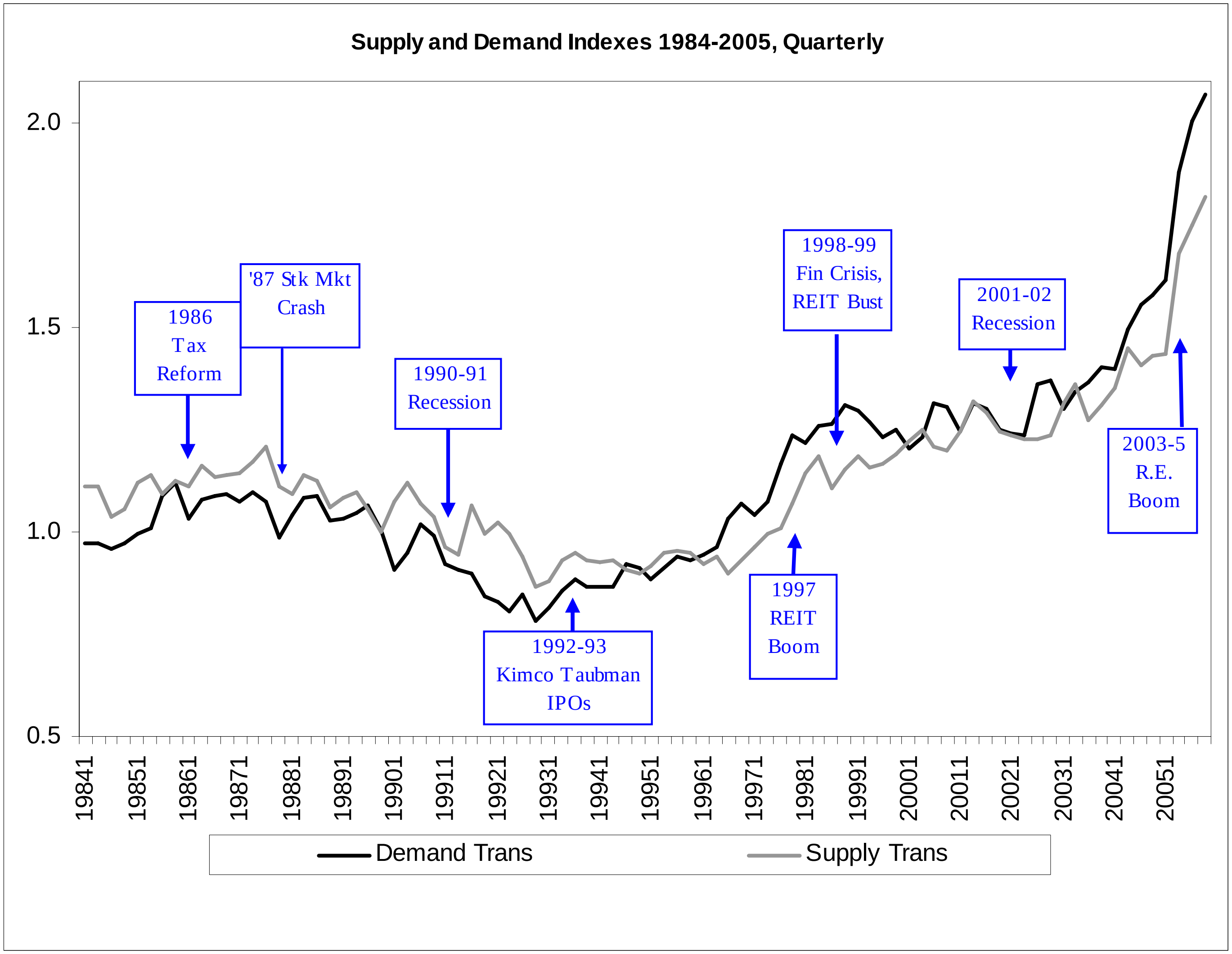


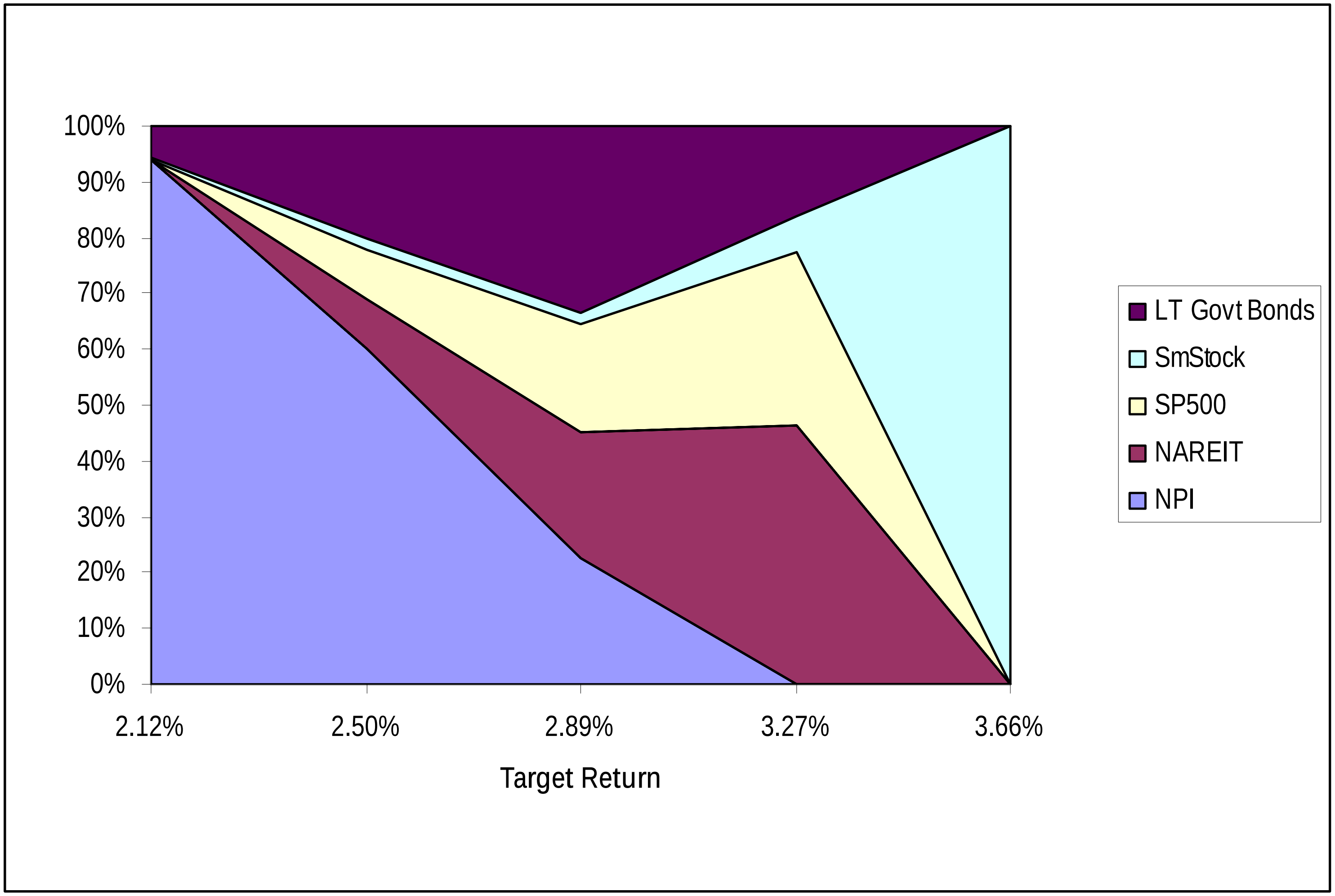
Exhibit 6

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

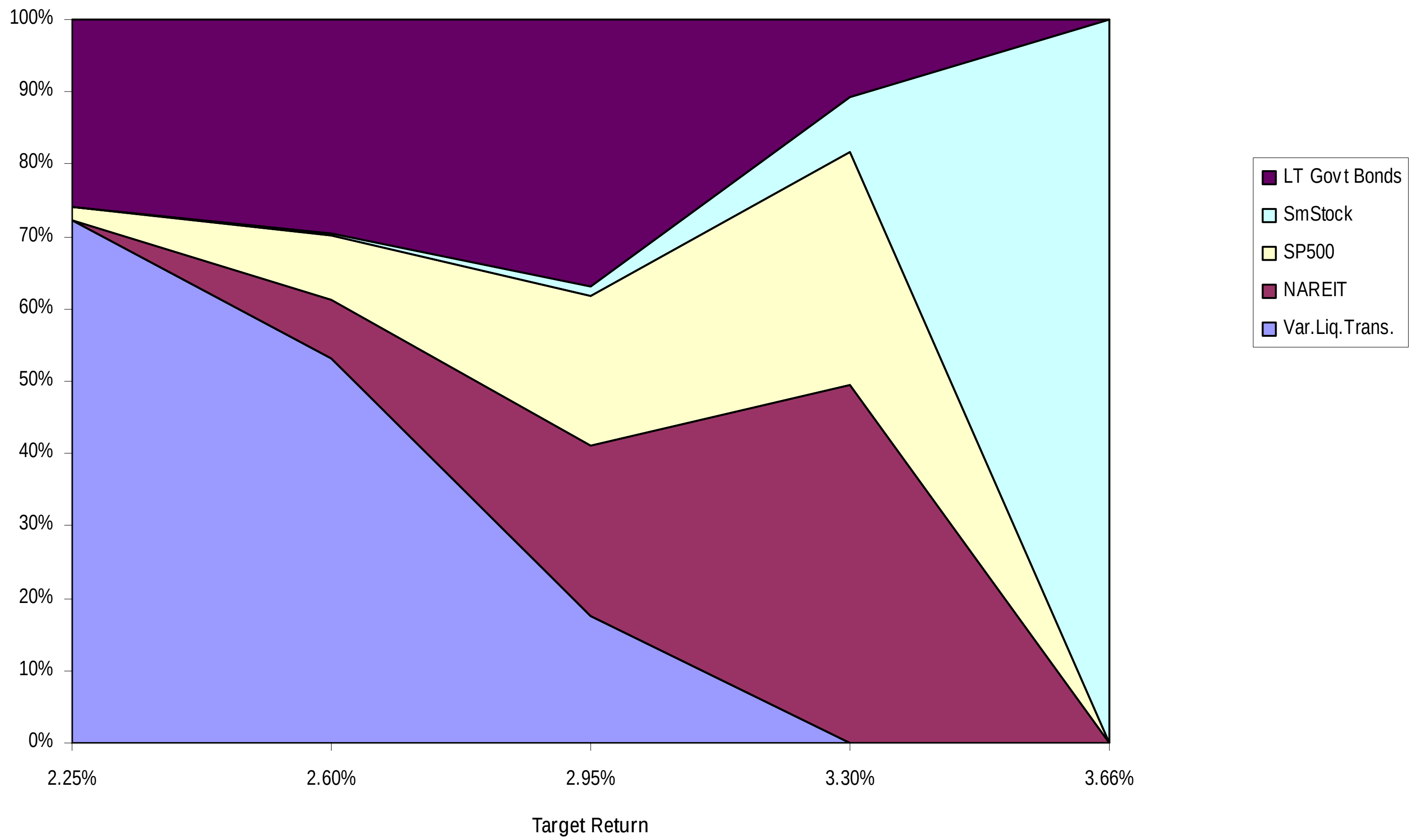


Exhibit 9: Sharpe-Maximizing Optimal Portfolio Shares under Two Different Private Real Estate Scenarios

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