REIT-Based Commercial Property Return Indices: A Model to Support and Improve Segment-Specific Investment in the Real Estate Markets

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Growing quantities of commercial property equity assets are being held by publicly traded securitized real estate companies, known as Real Estate Investment Trusts (REITS). Many practitioners in the investment industry, as well as academic economists, regard public stock exchanges to be more efficient and liquid than the traditional private property search markets in which whole real estate assets trade directly in privately negotiated transactions. Unfortunately, it has been cumbersome to fully utilize REITs' superior liquidity to make targeted property segment investments because of REITs' diversification and leverage.

Using REIT return data, bond data, and property holding data, we construct segment-specific indices of property market returns. We show that these deleveraged indices can be employed to make pure, targeted investments in the commercial real estate market while retaining the liquidity benefits of the well-developed public market in REITs. These new "pureplay" indices compare favorably with existing indices, displaying volatilities similar to existing transaction-based indices such as the Moody's/REAL CPPI. The pureplay indices can be generated at the daily frequency without significant increases in noise and at various levels of segment granularity. The new indices also appear to lead transactions-based direct property market indices during market turns. We find that the REIT-based Commercial Property Return Indices provide a unique, new information source about the commercial property market and a unique opportunity to make targeted investments, construct hedges in the real estate market, and support derivatives trading.

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Introduction

Investment in commercial real estate continues to grow, yet there is still a need to create tools to improve the liquidity and efficiency of trading in the commercial property asset class. This article examines how, using information from the REIT equity share market, it is possible to construct indices, or pure, targeted portfolios, that capture returns to the underlying properties while incorporating the efficiencies of the public stock market.

At the beginning of 2008, REITs owned approximately $600 billion of commercial real estate assets, about 10% to 15% of all tradable commercial real estate and over 20% of institutionally held property. At the same time, publicly traded equity REITs had a total market capitalization of approximately $289 billion[1]. We show that REITs own a reasonably representative sampling of properties such that careful manipulation yields information about the underlying property price process.

Geltner and Kluger originally proposed two methodologies for constructing property return indices using REIT data. In 1995, they offered a regression based approach wherein REIT returns are "delevered" and regressed against property holding data in a pooled regression[2]. Data limitations at the time of their analysis prevented the construction of a high frequency index. With the benefits of new, larger datasets, we refine and extend their analysis. We show that it is possible to create good-quality, high-frequency indices of property prices using REIT data.

In 1998, Geltner and Kluger offered a second approach; the "pureplay" methodology[3]. This approach constructed long and short portfolios with "pure" exposures to desired real estate segments using mathematical optimization. The pureplay approach also yielded promising results but, as with the previous model, a high frequency index could not be well-constructed due to limited data availability. A comparison of the pureplay with the regression approach reveals that, under certain conventional assumptions, the two methodologies yield mathematically identical results.

Several authors have offered approaches to building REIT indices specifically for hedging purposes. Giliberto[4] (1993) constructed a model to hedge some of the impact of stock market movements on REIT returns in order to isolate returns specific to real estate. Giliberto regressed REIT price changes on S&P 500 price changes. Using a methodology similar to Giliberto's, Liang, Chatrath, and McIntosh (1996) constructed a double-

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[1] Statistics provided by NAREIT.

[2] "A Regression-based Approach to Developing Historical Indices of Commercial Property Returns by Type of Property Based on REIT Share Returns", Geltner and Kluger, Paper presented at the AREUEA Annual Meeting, January 5-7, 1996, San Francisco

[3] "REIT-Based Pure-Play Portfolios: The Case of Property Types", David Geltner and Brian Kluger, Real Estate Economics, 1998 V26 4:pp. 581-612

[4] Giliberto, Michael. "Measuring Real Estate Returns: The Hedged REIT Index." The Journal of Portfolio Management: Vol. 19, Issue 3 (Spring 1993); pp.94-99

hedged index specifically for the apartment real estate segment[5]. Both of these models attempted to isolate real estate returns by regressing REIT returns on common market indices, using the regression residuals as measures of real-estate specific returns. However, to the extent that real estate prices are affected by factors that also affect the common market indices, important determinants of real estate prices would be removed from the resulting real estate indices if these hedging models were used as proxies for direct property investment. In other words, there is no reason to believe that true real estate returns are orthogonal to the stock market.

The Models

We explore three models for quantifying segment-specific returns in the real estate asset markets.[6] We first develop two regression models, a levered and a delevered model, that yield historical segment-specific return series for the U.S. Equity REIT market. The levered model attributes REIT returns to underlying property segment holdings without adjusting for debt held on REIT balance sheets. The delevered model adjusts for REIT debt holdings in order to produce implied property-level returns. We then examine a third approach, the pureplay approach, and show that, under conventional assumptions, it yields the same results as our delevered regression model. We evaluate model performance at monthly and daily estimation frequencies.

The first model, the *levered regression model,* attributes REIT equity price returns to specific market segments (for example, apartment, industrial, office, retail, and hotel). The estimated historical segment-specific returns are compared with the historical capitalization-weighted NAREIT/FTSE sector indices. The second regression model, the *delevered model,* does the same thing only at the property (asset) level. In the delevered model, estimated historical segment-specific returns are compared with the historical Moody's/REAL CPPI, a transactions price based (repeat-sales) index of U.S. commercial property price movements in the direct private property market.[7]

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[5] Liang, Chatrath, and MacIntosh. "Apartment REITs and Apartment Real Estate." The Journal of Real Estate Research: Vol. 11, Issue 3 (1996); pp. 277-290

[6] We use the term "segment" to refer to a combination of property usage type sector and geographical region that defines some segment of the overall aggregate commercial property market. From the perspective of institutional investment, the entire commercial property market (all income-producing investable properties) may be viewed as composing the investment "asset class". However, from the perspective of users of commercial space (the rental market) this aggregate of all property is actually a collection of numerous effectively geographically bounded specific property type markets (such as the Manhattan office market). Many investors in the real estate asset class like to target their investments based on some segmentation related to an understanding of the underlying rental markets. While the REIT-based indices presented here do not get down to the metro area level of granularity, they do provide substantial geographical and usage type segmentation, as we will see.

[7] The Moody's/REAL Commercial Property Price Index is based on data from Real Capital Analytics and methodology licensed by MIT to Real Estate Analytics LLC. It is produced and published monthly by Moody's Investors Service and is downloadable free from Moody's (www.Moodys.com).

The Levered Regression Model

The levered regression model is as described in Geltner and Kluger (1995) with some modification.[8] We regress the contemporaneous monthly REIT returns on a set of variables that represent proportional property segment holdings for each REIT. Rather than "pooling" observations over time as in Geltner and Kluger, we perform a separate regression for each period (monthly or daily) over the period January 1, 2001 to December 31, 2007[9]. For a capital return index, the dependent variable is the REIT price return, defined as:[10]

$$r_{i,t} = \frac{REIT\ price_{i,t} - REIT\ price_{i,t-1}}{REIT\ price_{i,t-1}} \tag{1}$$

where prices are fully adjusted for splits, etc. The return for REIT *i* is regressed on its exposures to each of its property segments. By changing the selection of explanatory segments, we can include more granular market segment holdings for more granular indices. We begin with five standard industry sectors and explore more granular segments later on in this paper.

Specifically:

$$r_{i,t} = b_{A,t}x_{A,i,t} + b_{O,t}x_{O,i,t} + b_{I,t}x_{I,i,t} + b_{R,t}x_{R,i,t} + b_{H,t}x_{H,i,t} + e_{i,t} \tag{2}$$

where:

$x_{A,i,t} =$ dollar percentage of assets held by REIT *i* in apartment segment at time *t*

$x_{O,i,t} =$ dollar percentage of assets held by REIT *i* in office segment at time *t*

$x_{I,i,t} =$ dollar percentage of assets held by REIT *i* in industrial segment at time *t*

$x_{R,i,t} =$ dollar percentage of assets held by REIT *i* in retail segment at time *t*

$x_{H,i,t} =$ dollar percentage of assets held by REIT *i* in hotel segment at time *t*

and where:

$$x_{Ai,t} + x_{O,i,t} + x_{I,i,t} + x_{R,i,t} + x_{H,i,t} = 1 \tag{3}$$

[8] The Geltner-Kluger 1995 working paper is available from the authors upon request.
[9] While running a pooled regression can sometimes provide more explanatory power than running separate regressions for each time period, separate regressions have the advantage of avoiding backward revisions in estimated returns in a production environment.
[10] Of course, a total return index is also possible.

In practice, many REITS have miscellaneous property exposures to segments not included in the model, such as land, garages, or international assets. We aggregate these miscellaneous property exposures into a single "other" segment and exclude any REITs having an "other" segment in excess of 30% of total property holdings. When "other" is less than 30% of total holdings, the REIT is included in the regression, the "other" exposure is ignored, and the remaining segment exposures are rescaled to sum to one. This treatment transfers the returns to the "other" property assets to the idiosyncratic return term (the error term). For example, if a REIT holds 25% office properties, 60% industrial properties, and 15% parking facilities, the office exposure is converted to 25/85% office, the industrial exposure is converted to 60/85% industrial, and the parking exposure is ignored thereby ensuring that the exposures always sum to one[11].

Using the levered model represented in equation (2), we generate coefficients for each month from 2001 through 2007. The estimated coefficients from the regressions are our estimated "segment returns". Equation (2) is thus similar to a classical APT multi-factor model of returns, although our purpose here is not to generate investment alphas but rather to attribute REIT returns to underlying property segments. For convenience, we rewrite the model in matrix notation (omitting the subscript t for clarity):

$$\boldsymbol{r}_{levered} = \boldsymbol{X}\boldsymbol{b}_{levered} + \boldsymbol{u} \qquad (4)$$

$\boldsymbol{r}_{levered}$ is a vector of length N, with each element representing the monthly return to each of the i=1...N REITs. $\boldsymbol{X}$ is an NxK matrix containing the dollar percentages of assets held by each REIT in each of the k=1...K segments (in the model described by equation (2), K is the 5th of 5 segments). In order to efficiently estimate the segment returns (the regression coefficients), we employ GLS weightings. We begin with a standard assumption that the variance of the idiosyncratic return, e_i , of a REIT is inversely proportional to the total dollar value of its property holdings, and that the idiosyncratic returns are uncorrelated, normally distributed, and have mean zero[12]. Intuitively, this weighting reflects the assumption that larger REITs are likely to have less idiosyncratic return variance because they have larger, more diversified portfolios of property holdings than smaller REITs. In other words, a type of heteroskedasticity exists in which smaller REITs have greater idiosyncratic variance.

We define Ω as an NxN diagonal matrix containing the idiosyncratic REIT return variances, with each diagonal element defined as:

$$u^2{}_{i,i} = \frac{1}{total_i} \qquad (5)$$

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[11] We experimented with models including the "other" segment, as in Geltner and Kluger's previous works, but found that the "other" term tended to behave like an intercept term (since virtually every REIT had at least some positive exposure to other miscellaneous segments) and therefore confounded the interpretation of the remaining coefficients.

[12] These assumptions are not necessary to construct our model using regression analysis, but relaxing these assumptions requires additional econometric manipulations not explored within the scope of this paper.

And where $total_i$ = total dollar value of properties held by REIT i. We also explore a common variation on (5) given by equation (6) below.

$$u^2_{i,i} = \frac{1}{\sqrt{total_i}} \tag{6}$$

Using generalized least squares, we estimate segment returns and weights for segment portfolios:

$$\hat{\boldsymbol{b}}_{\boldsymbol{levered}} = \left(\boldsymbol{X}^T \Omega^{-1} \boldsymbol{X}\right)^{-1} \boldsymbol{X}^T \Omega^{-1} \boldsymbol{r} \tag{7}$$

$$\boldsymbol{H}_{\boldsymbol{levered}} = \left(\boldsymbol{X}^T \Omega^{-1} \boldsymbol{X}\right)^{-1} \boldsymbol{X}^T \Omega^{-1} \tag{8}$$

$\boldsymbol{H}_{\boldsymbol{levered}}$ is a *KxN* matrix where each row *k* represents a portfolio of weights of REITs which has unit exposure (100% exposure) to segment *k* and zero exposure to every segment other than segment *k*. The segment portfolio weights sum to one for the target segment and to zero for the non-target segments, and may represent long and short positions. A segment portfolio, were it investable, would yield a pure return to the segment while minimizing idiosyncratic REIT return variance. We explain in a subsequent section how these segment portfolios are analogous to Geltner and Kluger's pureplay solution.

The levered model just described does not allow us to fully draw conclusions about the underlying property market because REITs are typically levered, holding anywhere from zero debt to over 50% debt. While underlying property price movements are reflected in the estimated levered segment returns, the levered segment returns are much more volatile than underlying property returns. Because it is our aim to estimate underlying property returns, we build a second regression model: the delevered regression model.

The Delevered Regression Model

The basic structure of the delevered model is the same as the levered model with the exception of important adjustments to the REIT returns. Rather than using unadjusted price returns as our dependent variable, we delever the returns using the Weighted Average Cost of Capital (WACC) accounting identity:

$$roa_{i,t} = \left(\%equity_{i,t}\right) \cdot r_{i,t} + \left(\%debt_{i,t}\right) \cdot debtrate_t \tag{8}$$

In this form, the same debt rate is used for all REITs[13]. In practice, converting REIT price returns to returns on the underlying assets free and clear (*ROA*) is not an exact process. We describe our approach in the data section of this paper.

[13] This form could be revised to incorporate unique debt rates at the REIT level.

After adjusting the observed REIT returns for leverage using equation (8), the form of the regression becomes (again, omitting a subscript for time)[14]:

$$\boldsymbol{roa} = \boldsymbol{Xb}_{\boldsymbol{delevered}} + \boldsymbol{u} \tag{9}$$

$$\hat{\boldsymbol{b}}_{\boldsymbol{delevered}} = \left(\boldsymbol{X}^{\boldsymbol{T}}\Omega^{-1}\boldsymbol{X}\right)^{-1}\boldsymbol{X}^{\boldsymbol{T}}\Omega^{-1}\boldsymbol{roa} \tag{10}$$

$$\boldsymbol{H}_{\boldsymbol{delevered}} = \left(\boldsymbol{X}^{\boldsymbol{T}}\Omega^{-1}\boldsymbol{X}\right)^{-1}\boldsymbol{X}^{\boldsymbol{T}}\Omega^{-1} \tag{11}$$

In this revised form, the estimated coefficients directly reflect the returns to the underlying property segments. The segment portfolios contained in $\boldsymbol{H}_{\boldsymbol{delevered}}$ do not include the debt positions needed to offset the leverage held by the REITS, because that leverage has already been removed form the dependent variable (*roa*). Therefore, and interestingly, note that equation (11) is identical to equation (8). This implies that the optimal relative weights of the REITs in the segment portfolio are independent of leverage and the techniques used to deleverage the REIT returns. It also implies that, were an investor to purchase the "segment portfolio", or a constrained version of it, it would be possible to synthetically add or subtract leverage by appropriately scaling the portfolio weights. In order to generate the portfolio of assets that would theoretically need to be purchased to obtain underlying property segment-specific returns, completely adjusting for leverage, the segment portfolios need adjustment. These adjustments can be accomplished by returning to the WACC identity for each REIT:

$$hadjusted_{k,i} = (\%equity_i) \cdot h_{k,i} \tag{12}$$

$$debtoffset_{k,i} = \left(\%debt_i\right) \cdot h_{k,i} \tag{13}$$

where $h_{k,j}$ is the share (long or short) of the pureplay portfolio for target segment k to be invested in REIT j.

A third methodology for constructing segment specific returns is the pureplay portfolio approach. First presented by Geltner and Kluger in 1998, the form of the pureplay model is as follows (following Geltner and Kluger's notation):

[14] In Geltner and Kluger, the dependent variable is originally defined as ROA, but prior to regression is then divided by (equity/totalassets) yielding the REIT return plus a function of debt. Therefore, the observed coefficients cannot be directly interpreted as the segment-specific ROAs without further manipulation. In an effort to produce coefficients that translate directly into segment-specific ROAs, the dependent variable is preserved as ROA. ROA is then regressed on explanatory variables, namely the relative dollar investments in each segment. The coefficients can be interpreted directly as segment specific ROAs. Essentially, we ran the regression directly using equation (3) from Geltner and Kluger's paper using ROA as defined above.

$$\tilde{r}_i = x_{A,i}\left(\tilde{r}_A + \tilde{e}_{A,i}\right) + x_{O,i}\left(\tilde{r}_O + \tilde{e}_{O,i}\right) + x_{I,i}\left(\tilde{r}_I + \tilde{e}_{I,i}\right) + \ldots + x_{K,i}\left(\tilde{r}_K + \tilde{e}_{K,i}\right) \tag{15}$$

where:

$r_i =$ observed return to REIT i
$\tilde{r}_k =$ pureplay return to segment k
$x_{k,i} =$ fraction of REIT i invested in segment k
$\tilde{e}_{k,i} =$ idiosyncratic return to REIT i's property in segment k

and again:
$$\sum_K x_{k,i} = 1$$

where K denotes the last of some number of segments. In our previous segment model of equation (2), the Kth segment is the 5th of five segments. Notice that equation (15) does not look altogether different from equation (2) except for the specification of the error terms (the idiosyncratic returns).

The idiosyncratic components in the pureplay model are assumed to be random, uncorrelated with each other, and have mean zero. Define a pureplay portfolio as a portfolio with unit exposure to the desired segment and zero exposure to all other segments:

$$\tilde{r}_p = \tilde{r}_A \sum_{i=1}^{N} w_i x_{A,i} + \tilde{r}_O \sum_{i=1}^{N} w_i x_{O,i} + \ldots + \tilde{r}_K \sum_{i=1}^{N} w_i x_{K,i} + \sum_{i=1}^{N}\left(w_i x_{A,i} e_{A,i} + \ldots + w_i x_{K,i} e_{K,i}\right) \tag{16}$$

where each w_i equals the percentage of the portfolio's holdings in REIT i and where the constraints for a pureplay portfolio for a single segment k can be written mathematically as:

$$\sum_{i=1}^{N} \sum_{j \neq k} w_i x_{i,j} = 0 \tag{17}$$

$$\sum_{i=1}^{N} w_i x_{i,k} = 1 \tag{18}$$

Substituting the constraints (17) and (18) into equation (16) yields a simplified equation for the return to the pureplay portfolio for segment k:

$$\tilde{r}_p = \tilde{r}_k + \sum_{i=1}^{N}\left(w_i x_{A,i} e_{A,i} + \ldots + w_i x_{K,i} e_{K,i}\right)$$
(19)

the variance of which is given by:

$$VAR(\tilde{r}_p) = VAR(\tilde{r}_k) + \sum_{i=1}^{N}\left(w_i^{\,2} x_{A,i}^{\,2} VAR(e_{A,i}) + \ldots + w_i^{\,2} x_{K,i}^{\,2} VAR(e_{K,i})\right) \qquad (20)$$

In Geltner and Kluger (1998), the authors assume that the idiosyncratic segment variance is inversely proportional to a REIT's dollar holdings in that segment (recall that this assumption is similar to, but not identical to, the assumption used in the GLS model, equation (5)). Specifically:

$$VAR(e_{k,i}) = \frac{1}{x_{k,i} \cdot total_i} \qquad (21)$$

If we substitute the values from (21) into equation (20), we can simplify the minimization problem somewhat more:

$$VAR(\tilde{r}_p) = VAR(\tilde{r}_k) + \sum_{i=1}^{N}\left(w_i^{\,2} x_{A,i}^{\,2} \frac{1}{x_{A,i} \cdot total_i} + \ldots + w_i^{\,2} x_{k,i}^{\,2} \frac{1}{x_{k,i} \cdot total_i}\right) \qquad (22)$$

which reduces to:

$$VAR(\tilde{r}_p) = VAR(\tilde{r}_k) + \sum_{i=1}^{N}\left(w_i^{\,2} \cdot \frac{1}{total_i}\right) \qquad (23)$$

As we differentiate equation (23) with respect to the w_i for the purposes of minimization, it becomes clear that the solution is a function of just the second term.

Because of our assumptions regarding idiosyncratic returns, the variance of the idiosyncratic returns in the pureplay model reduces to the same variance assumption used in our GLS regression models. Recall that the estimated GLS coefficient vector minimizes the sum of the squared errors of the regression. In other words, it minimizes the variance of the error terms (the idiosyncratic returns)[15]. In the case of the GLS regression models, these variances are assumed values contained in Ω which were defined in equation (5). Therefore, the GLS solution yielding $\boldsymbol{H}_{delevered}$ is identical to the solution to minimizing equation (23) with respect to the w_i. As a result, it is not necessary to develop both frameworks under the current set of assumptions. Therefore, we proceed with the traditional regression framework because the vocabulary is consistent with most of the existing methodologies currently used in the field of portfolio management.

[15] as long as we continue to assume the idiosyncratic returns are random, are uncorrelated, and have mean zero

Experimenting with Model Granularity

After completing both regression models for five major industry segment types, we explore the feasibility of adding geographic regions to the models. First, we construct a regional model using only geographic data for the explanatory variables. For each REIT, we calculated the percentage of properties held in the West, Midwest, East, and South regions as defined by NCREIF.[16] Our independent variables in the regional model are defined as:

$x_{Wi,t}$ = dollar percentage of assets held by REIT *i* in the West region at time *t*

$x_{MW,i,t}$ = dollar percentage of assets held by REIT *i* in the Midwest region at time *t*

$x_{E,i,t}$ = dollar percentage of assets held by REIT *i* in the East region at time *t*

$x_{S,i,t}$ = dollar percentage of assets held by REIT *i* in the South region at time *t*

And again:

$$x_{Wi,t} + x_{MW,i,t} + x_{E,i,t} + x_{S,i,t} = 1 \quad (24)$$

Finally, we construct a model using both property usage type sectors and geographic location information[17]. To do this, we expand the number of independent variables from five to twenty. For the apartment segment, for example, the original definition for the apartment segment variable

$x_{A,i,t}$ = dollar percentage of assets held by REIT *i* in apartment segment at time *t*

is replaced with four new variables:

$x_{W,A,i,t}$ = dollar percentage of assets held by REIT *i* in the west in apartment segment at time *t*

$x_{S,A,i,t}$ = dollar percentage of assets held in the south in apartment segment at time *t*

$x_{E,A,i,t}$ = dollar percentage of assets held in the east in apartment segment at time *t*

$x_{MW,A,i,t}$ = dollar percentage of assets held in the Midwest in apartment segment at time *t*

We also explore adding only subsets of the four regions to the models. The results of these trials are presented in the application section of this paper.

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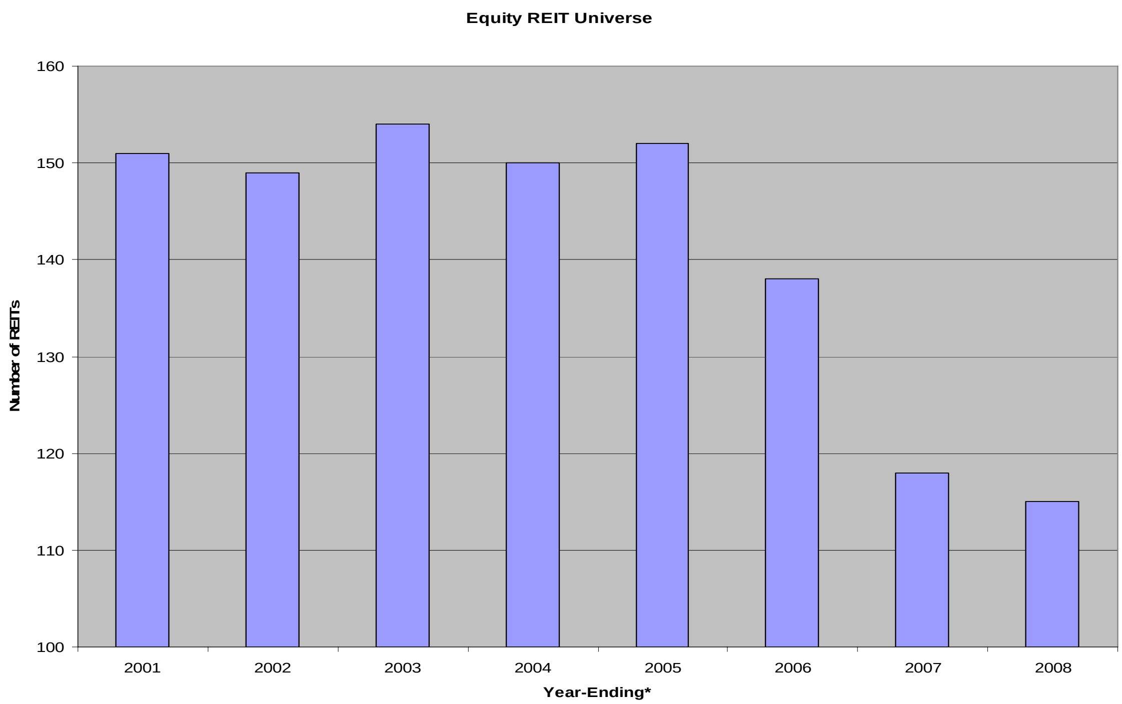
[16] NCREIF is the National Council of Real Estate Investment Fiduciaries (www.ncreif.org). As the NCREIF Property Index (NPI) is currently the most widely used index of U.S. commercial real estate investment performance, it seems useful to base regional definitions on the NCREIF regions. These differ from US Census definitions, reflecting institutional real estate investment patterns.
[17] using NCREIF's geographic definitions for West, Midwest, South, and East.

Data

We study publically traded equity REITS during the period 2001-2007 using as our universe the REITs listed in the NAREIT/FTSE indices. Table (1) below shows the numbers of publically traded equity REITs in each of the NAREIT/FTSE indices during the study period. The decline in publicly traded equity REITS in 2006, 2007 and into 2008 is caused both by a decrease in IPO's and a flurry of privatizations.

Table (1)



Using property holding information supplied by NAREIT along with data pulled from public SEC 10k filings, we calculate the independent variables needed for the models for each month. Charts (1)-(5) below show the distributions of the industry-segment exposures (denoted *exp*) for the first and last years in our study period.

Chart (1)

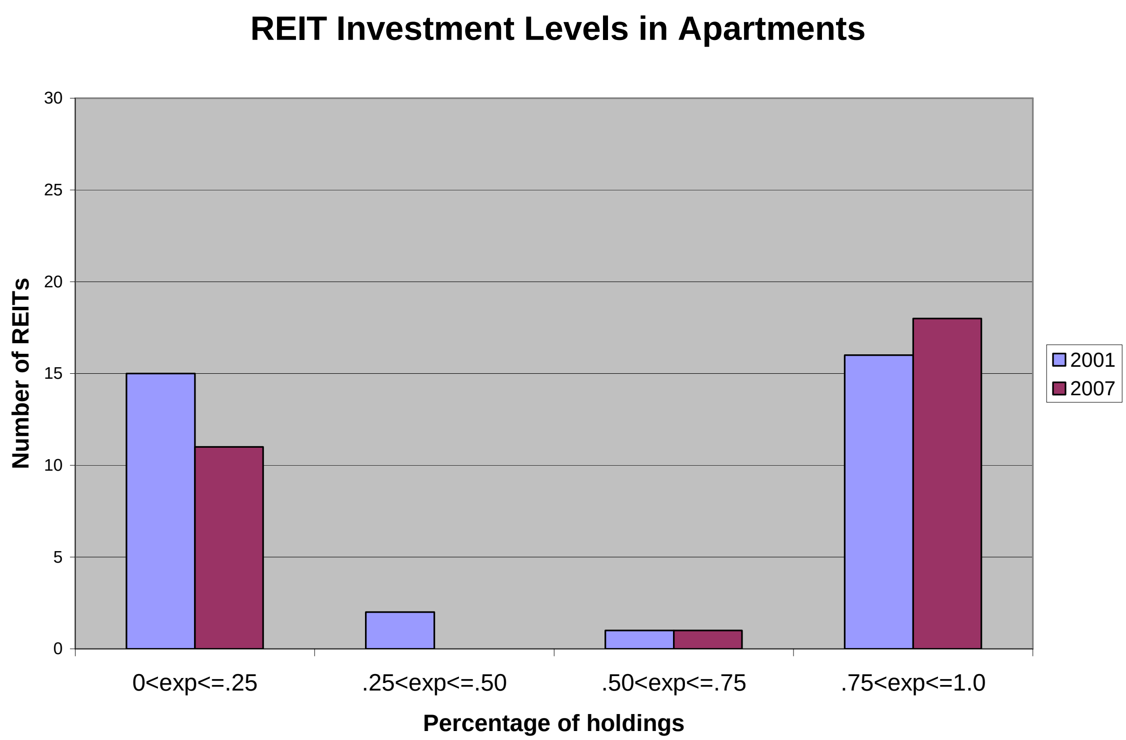


Chart (2)

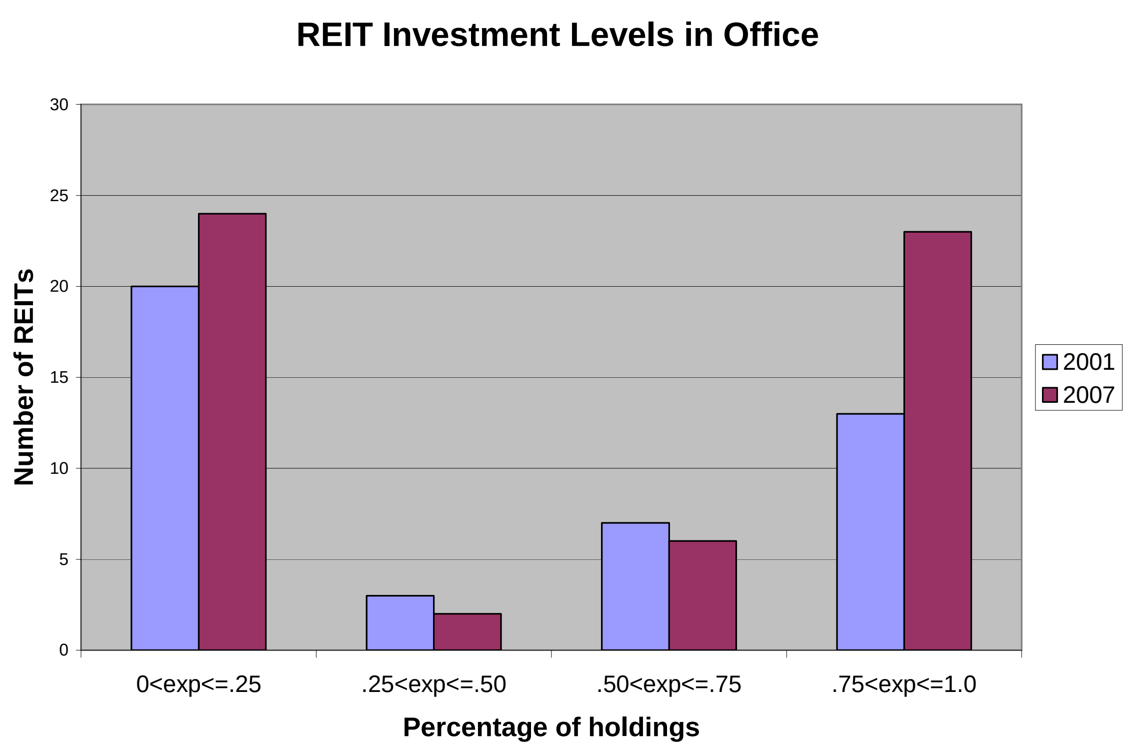


Chart (3)

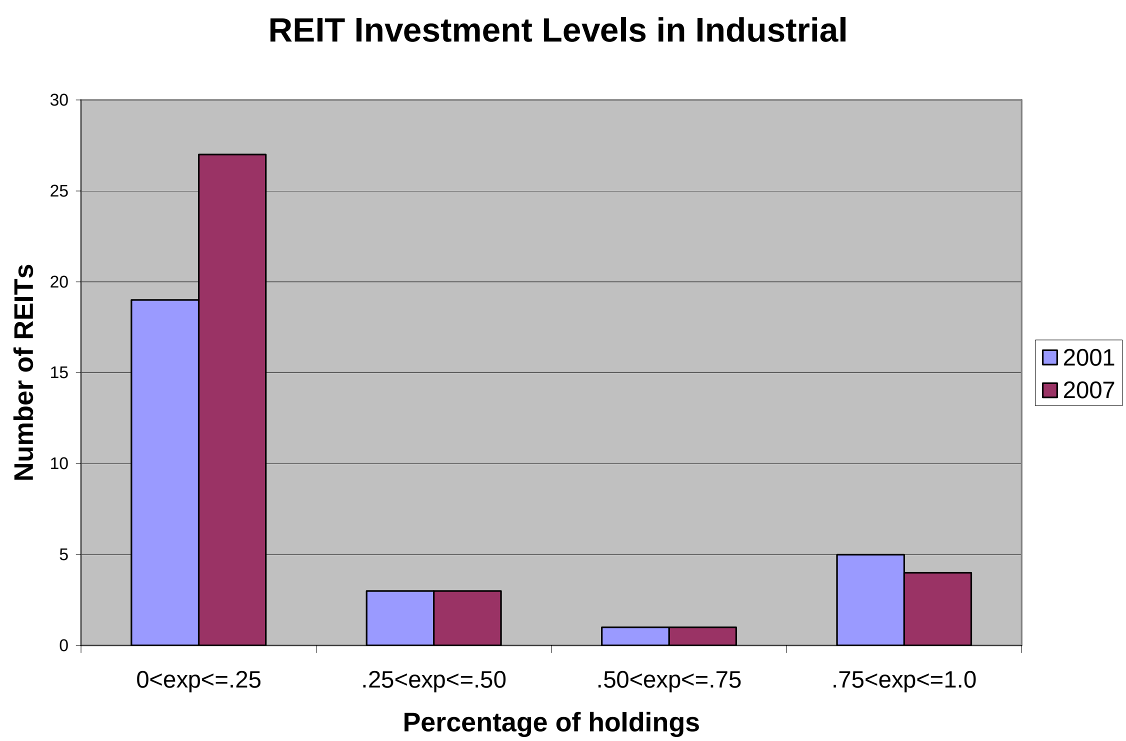


Chart (4)

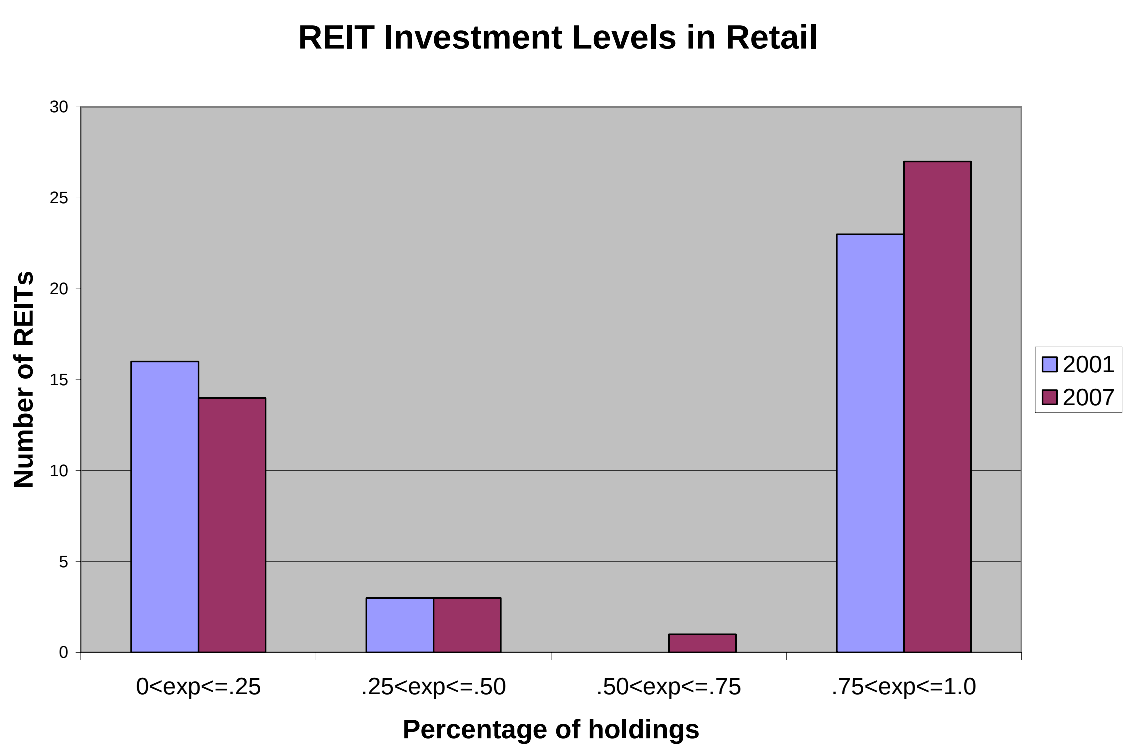
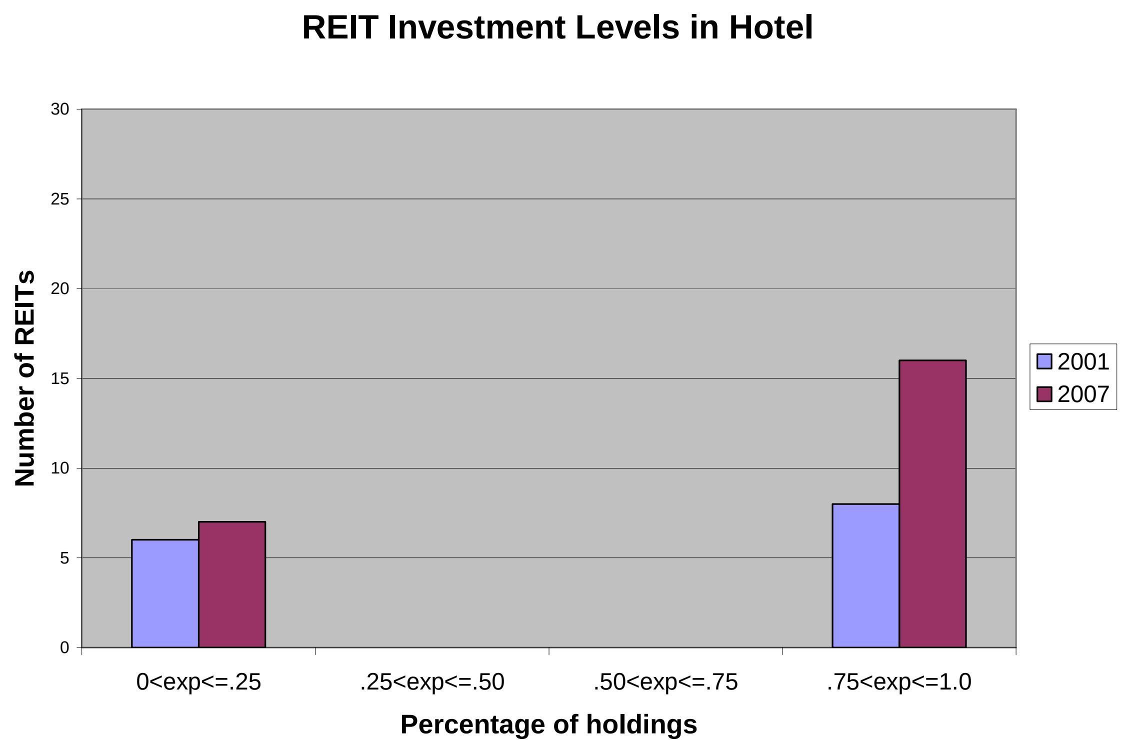


Chart (5)



Where the dollar value of assets in a REIT's portfolio is unknown, proxies for property value such as rental income or total square footage are used to calculate the percentage holdings in the various market segments[18]. Few REITs diversify equally across industries. For example, it is unusual to find a REIT with 25% of its holdings in apartment, 25% in industrial, 25% in retail, etc. However, most REITs have at least some small exposure to sectors outside their primary type. Hotel/Lodging REITs tend to be the most highly focused. In fact, in the application section of this paper, we will show that the hotel exposure variable is nearly orthogonal to the other independent variables.

From examining charts (1)-(5), we can see that classifying REITs into categories without accounting for small segment holdings ignores a good deal of valuable information. The regression models presented here are able to keep and utilize all of the property holding information, even the smaller exposures By contrast, the NAREIT/FTSE sectoral indices categorize a REIT into a sector if the REIT's property holding in the sector is 75% or more of its total property holdings. For example, a REIT is included in the NAREIT/FTSE Retail Index if 75% or more of its properties are in the retail sector. A REIT whose retail properties comprise only 60% of its portfolio is excluded from the retail index despite the fact that the majority of its property exposure is in the retail sector. This convention applies to all of the NAREIT/FTSE indices.

[18] We checked the validity of this assumption by comparing changes in exposures using various methodologies on REITs for which multiple types of data were available.

Using the same property holding data, we generate the independent variables for the regional model according to equation (24). The regions West, Midwest, East, and South are defined using NCREIF's convention. The distributions of independent variables are reported in charts (6)-(9).

Chart (6)

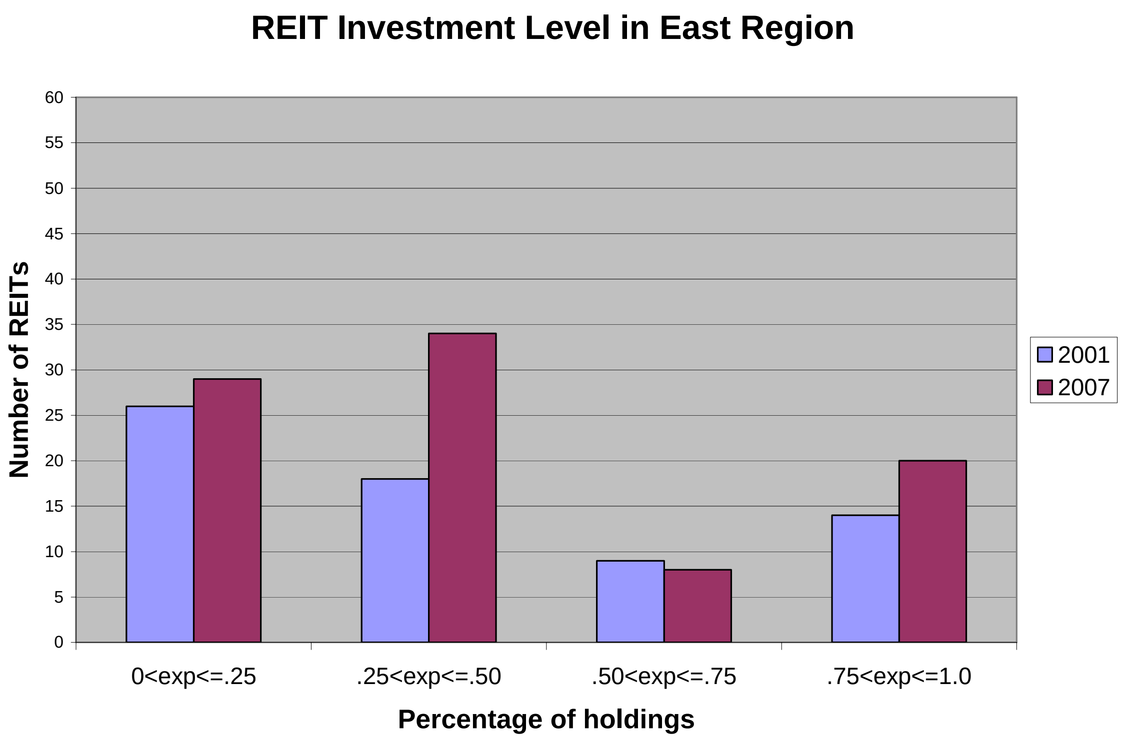


Chart (7)

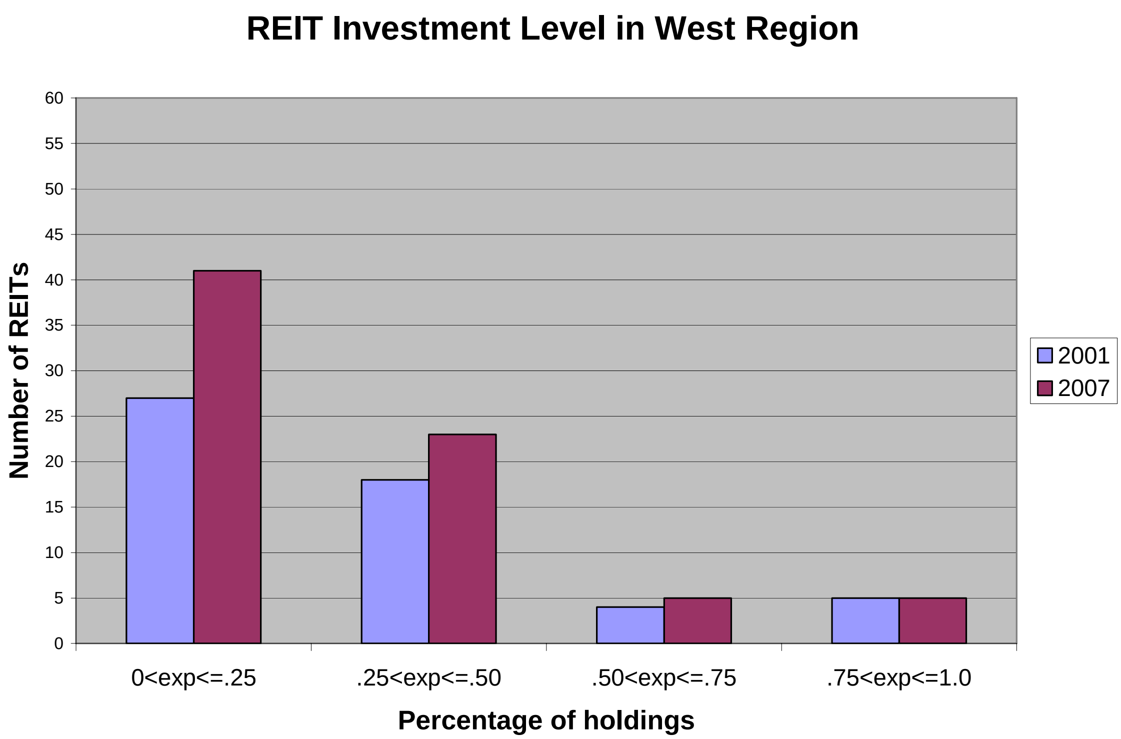


Chart (8)

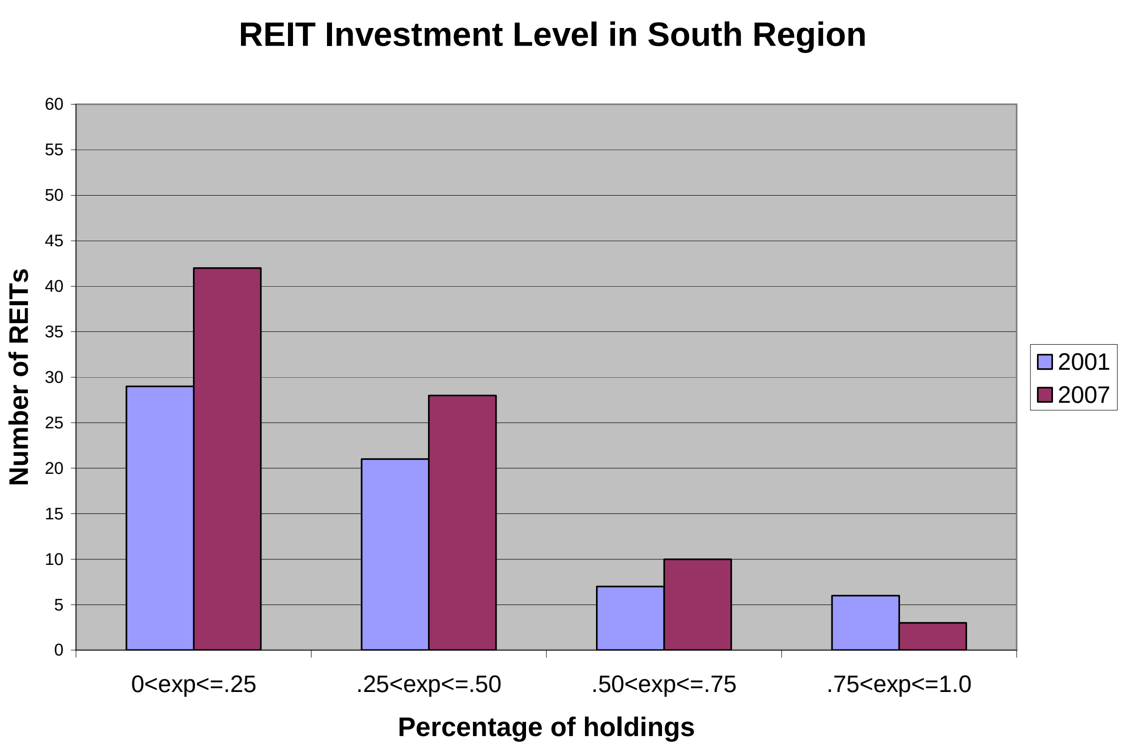
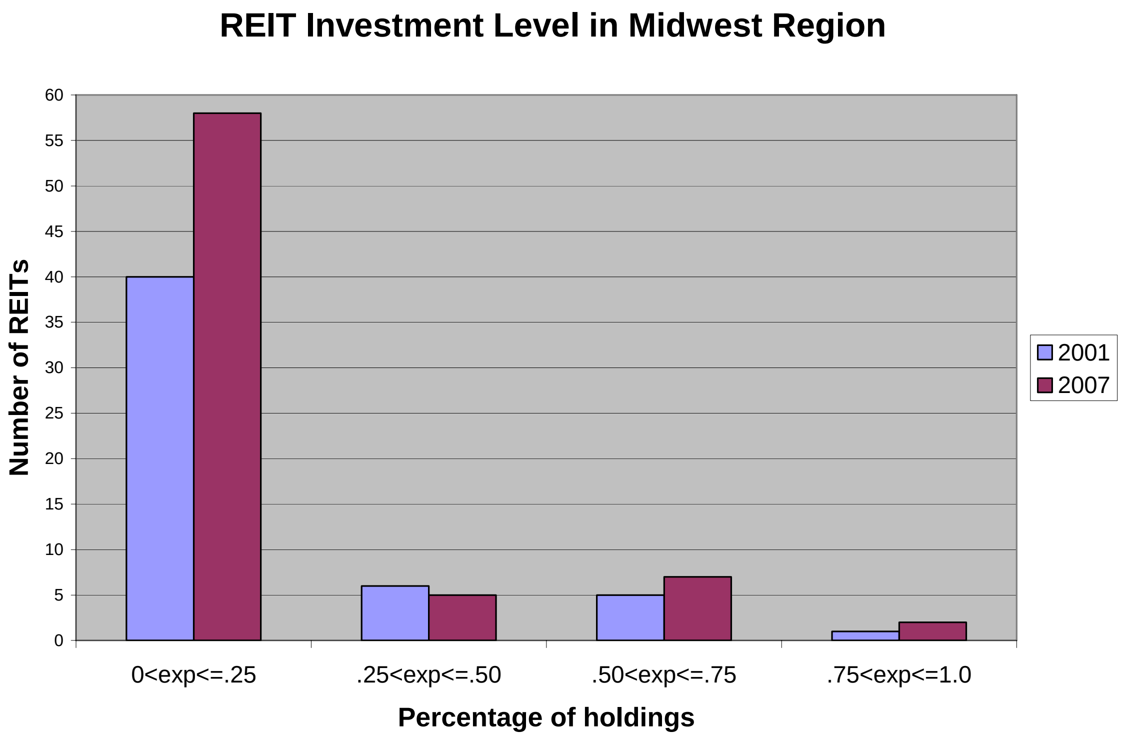


Chart (9)



REITs are typically geographically diversified, in contrast to their tendency to specialize in particular industry segments.

Finally, we generate independent variables for the twenty-segment model described on page 9. Appendix Charts (A1)–(A20) show the number of REITs with various levels of exposure to each of the twenty segments. Charts (A11) and (A12) show that few REITs have significant exposure to the Industrial South segment and the Industrial Mid West segment. Appendix Charts (A17)-(A20) show that many of the regional Hotel segments are also not well represented in the data. As we discuss later in the application portion of this paper, several of these segments are recombined in order to create stable regression estimates.

Return data for the REITs was supplied by NAREIT. We utilize price-only returns (excluding dividends), so as to track property price movements.[19] Returns were reviewed for data errors but none were culled or truncated as outliers.

Using financial information from NAREIT and from annual 10k forms, we generate values for the %equity and the %debt held by each REIT. The %equity (also referred to as the equity ratio) is defined as total stockholder's equity divided by the sum of total stockholders equity and total liability as of the year-end date on 10k forms. The

[19] As noted previously, however, the methodology described here could as easily be applied to total returns data, to yield total return property indexes.

equity ratio data is updated annually for each year in the study. We do not adjust for possible minority interest holdings because, during the study period, minority interests were relatively insignificant on most balance sheets. In the future, minority interests may become more significant on a greater number of the REITs' balance sheets and would therefore warrant closer attention. Equity ratios remained fairly stable during this period with a mean and median of 36% in 2001 and 2007 and a range from 7% to 83% in 2001 and from 7% to 76% in 2007.

Referring again to equation (9), we need an estimate for the cost of debt in order to complete the deleverage calculation. Pagliari, Scherer, & Monopoli (2005)[20] proposed that the cost of debt can be estimated as:

$$debtrate_{i,t} = (IE_{i,t} + PD_{i,t})/(.5(TD_{i,t} + TD_{i,t-1}) + .5(PS_{i,t} + PS_{i,t-1})) \qquad (25)$$

where:

$IE_{i,t}$ = the interest expense for firm i in period t

$PD_{i,t}$ = the preferred dividends paid by firm i in period t

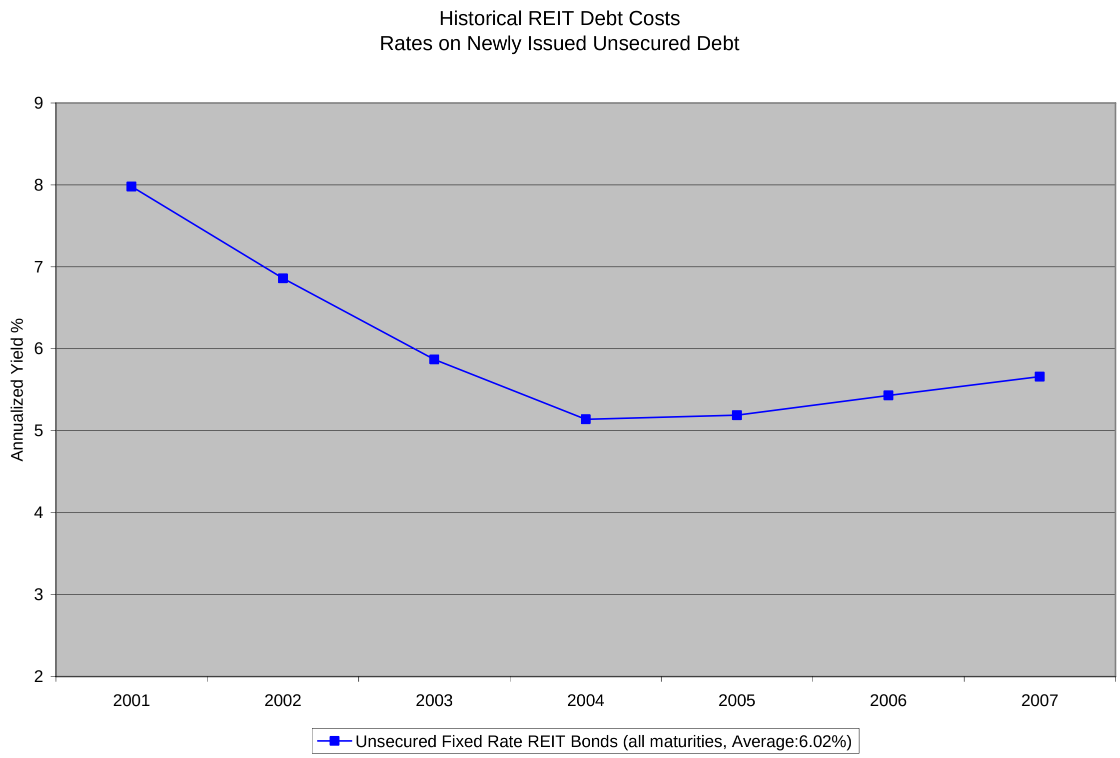
$TD_{i,t}$ = firm i's total debt balance (book value) in period t

$PS_{i,t}$ = firm i's preferred stock at the end of year t

In this paper, we choose to use market-wide average yields on unsecured REIT debt as a proxy for the cost of debt, with the same rate applied to every REIT for the year. Some REITs report their weighted average cost of debt in their annual 10k filings. A comparison of the self-reported average costs of debt with the estimated values in the charts below indicates that our estimates are reasonable. For example, in 2007, Boston Properties reported a weighted average cost of debt of 5.60%. Mack-Cali Realty reported a value of 6.08%. The model uses a value of 5.66% in 2007 for all REITs. While the deleveraging process would be more precise if REIT-specific values were obtained, we defer this refinement for future research. As mentioned in the previous section of this paper, assumptions regarding cost of debt can be varied without changing the composition of the delevered segment portfolios defined by equation (11).

[20] "Public versus Private Real Estate Equities: A more refined, Long-Term Comparison." Real Estate Economics, 2005 V33, pp.147-187

Chart (10)



Application

We begin by running the GLS regressions described by equation (2) separately for each of the eighty four months spanning 2001-2007. Next, we run the GLS regressions for the delevered model, described by equations (8)-(11). We accumulate the estimated segment returns and plot them against the equivalent Moody's/REAL CPPI index. The correspondence between the REIT-based and Moody's/REAL price indexes in charts (11)-(15) suggests that the REIT-based indices are indeed accurately reporting segment-specific returns to the underlying property market. The REIT-based indices compare favorably with the corresponding Moody's/REAL indices in tracing transaction prices in the direct private property market in the sense that the corresponding indexes are largely similar, but with differences that are interesting and make sense, as described below.

Chart (11)

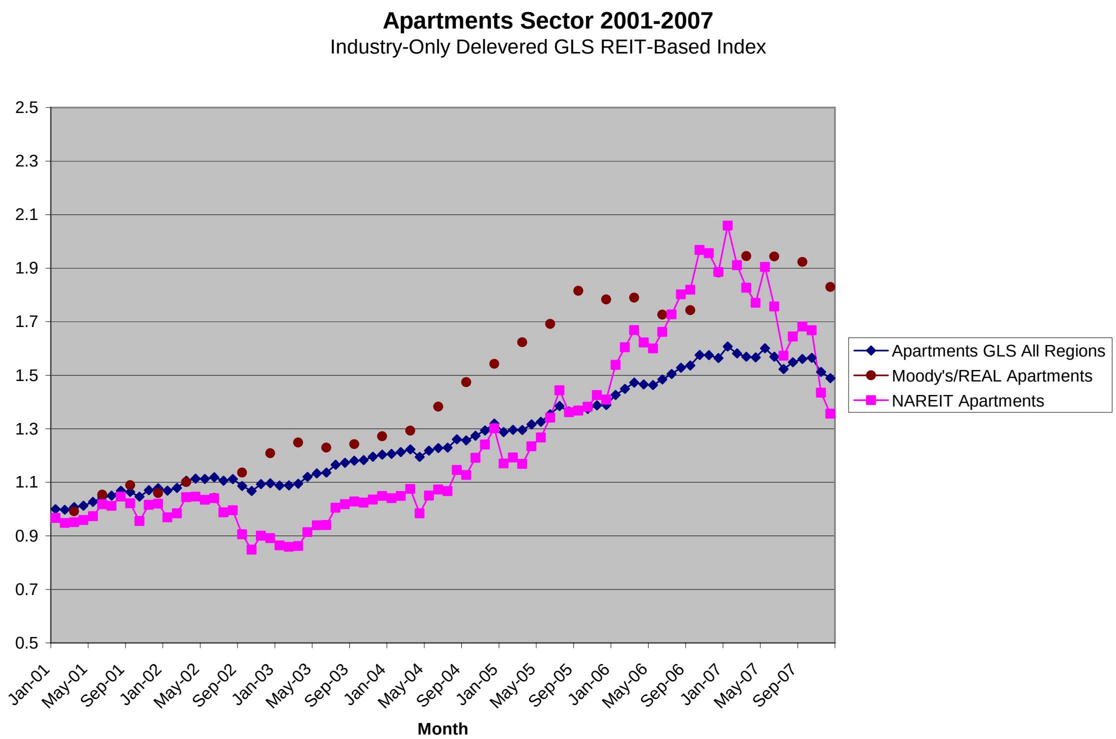


Chart (12)

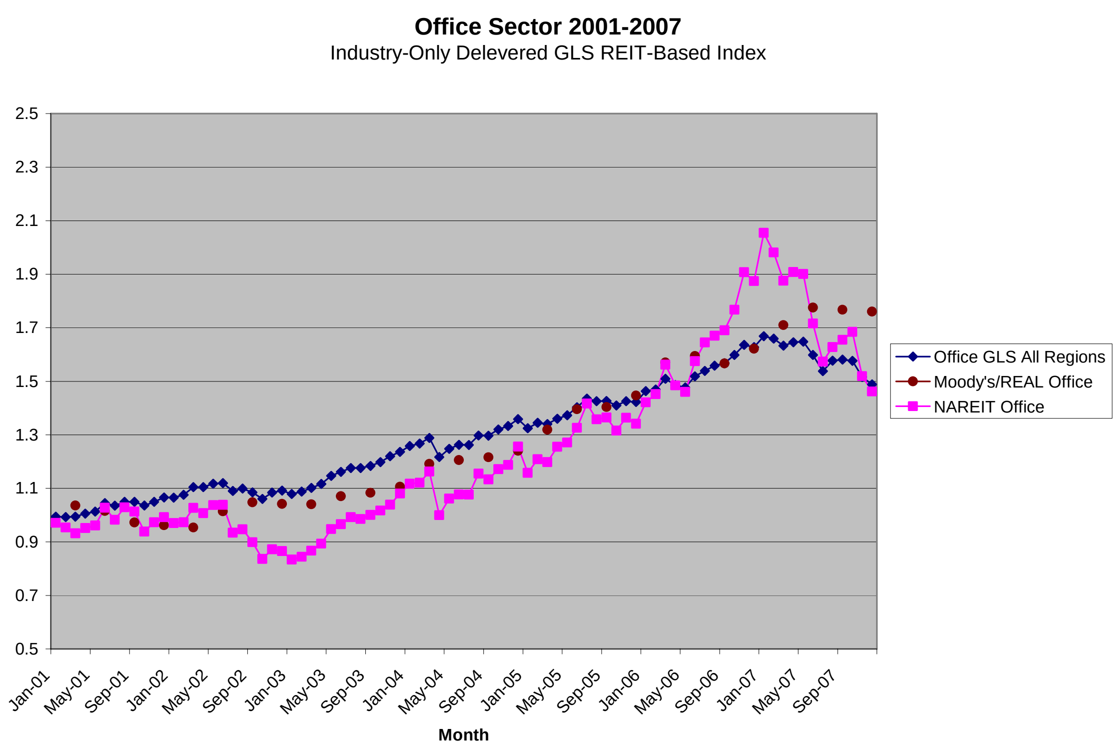


Chart (13)

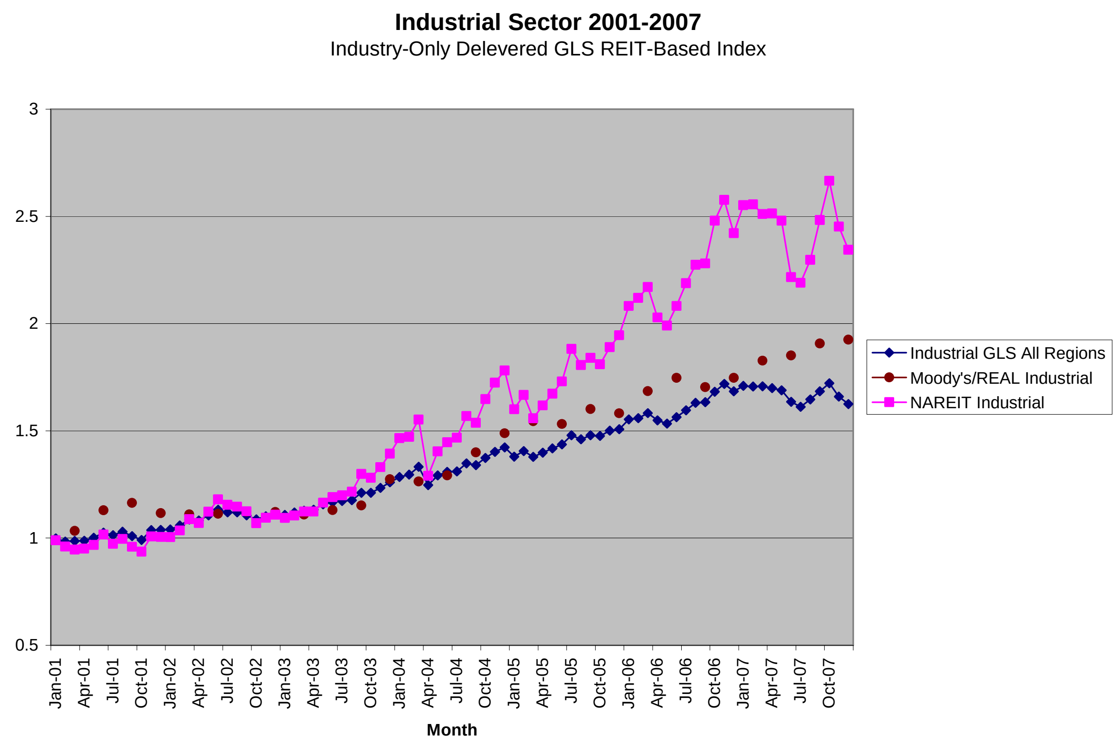


Chart (14)

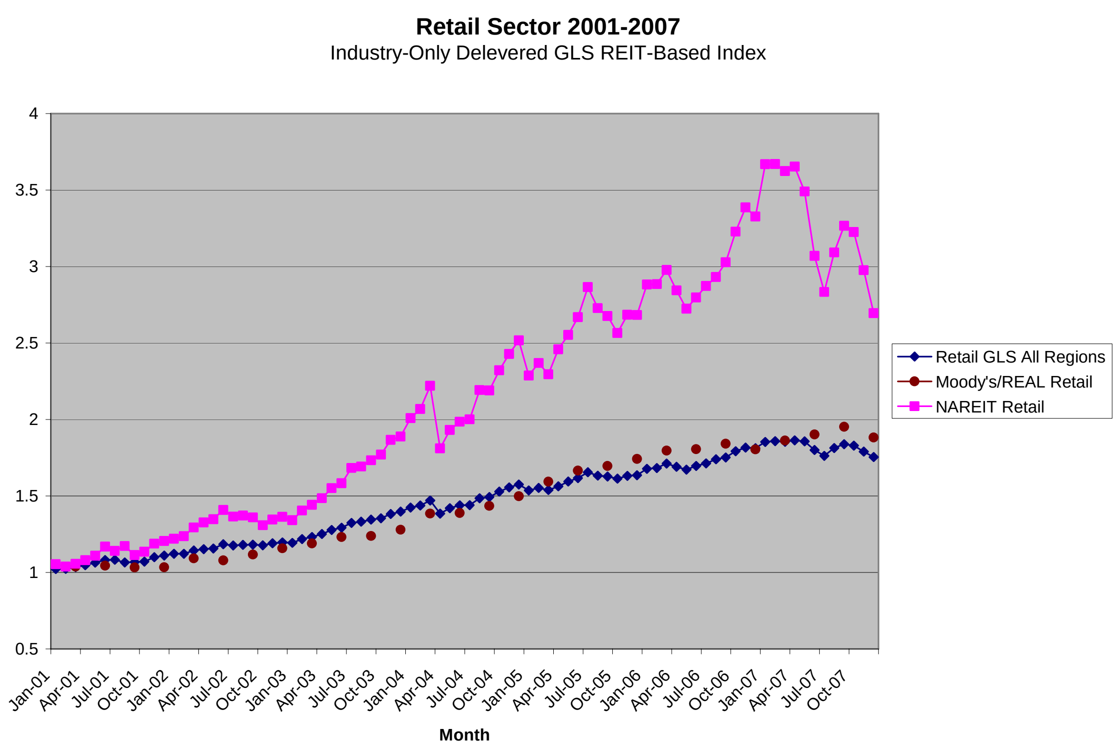


Chart (15)

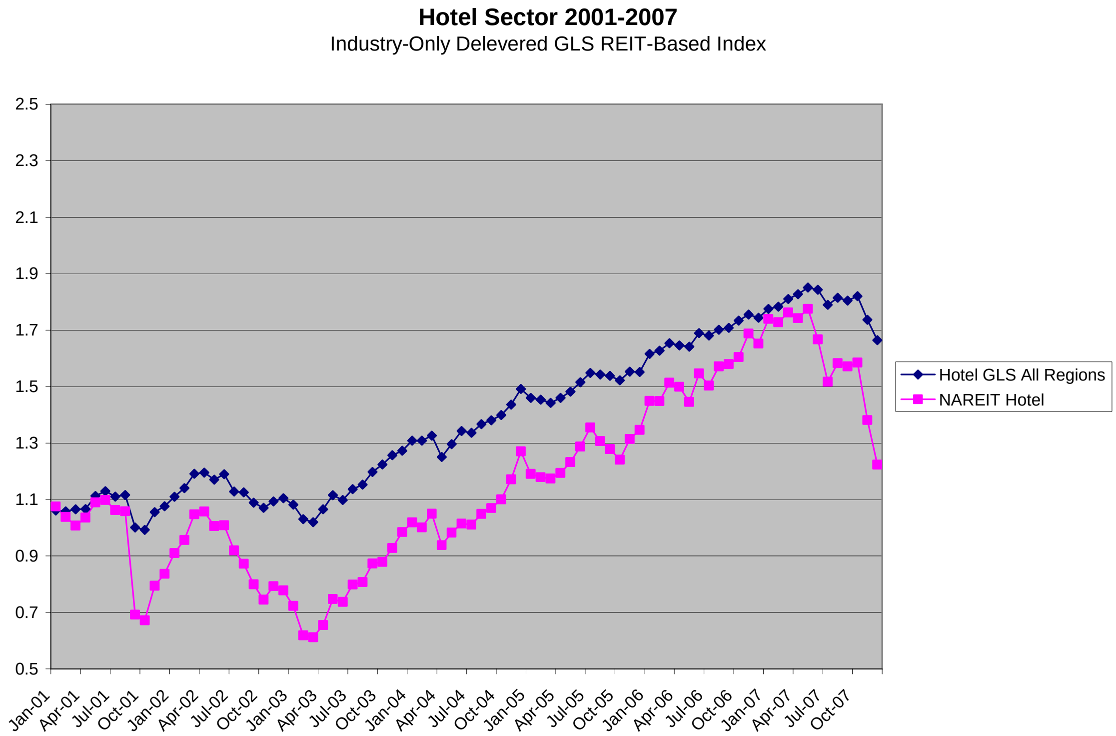
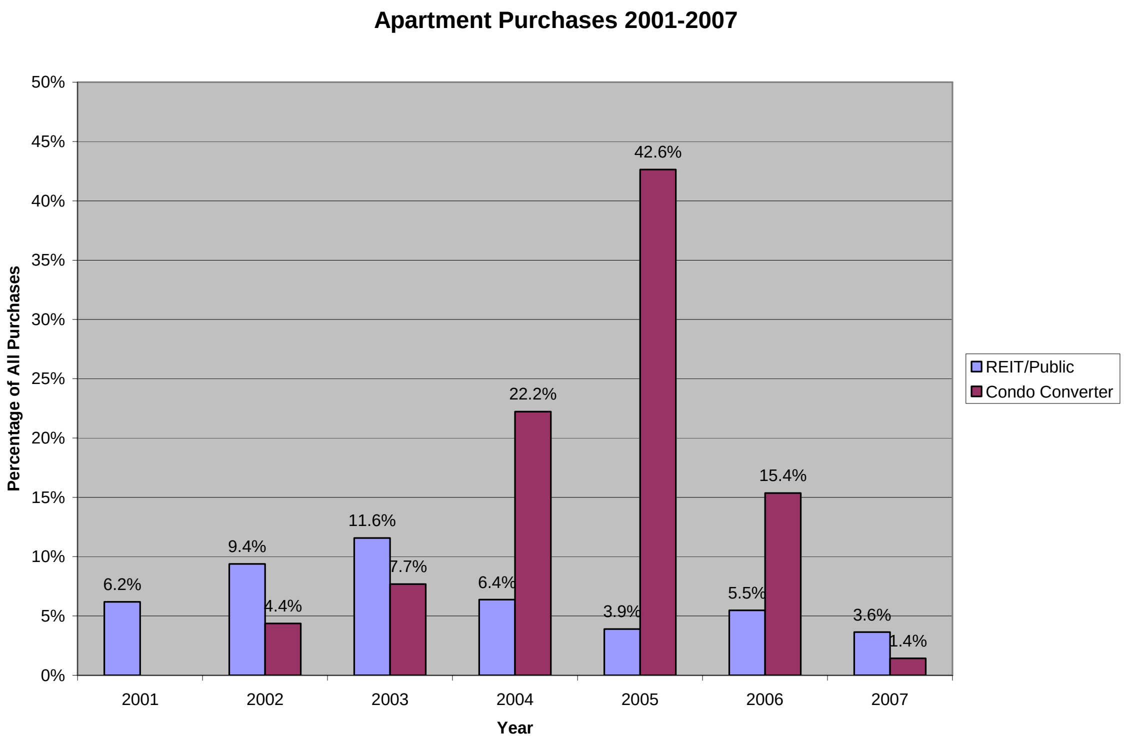


Chart (16)[21]



[21] Apartment sector purchase data is obtained from the Real Capital Analytics databases.

For each sector except apartment/residential, the REIT-based estimated delevered segment returns resemble the corresponding Moody's/REAL price changes. Of course we would not expect the two types of indexes to be identical, as they are not tracking exactly the same property markets, and the stock market does not evaluate property in exactly the same way that the private direct market does. (Indeed, this is one of the major motivations for the REIT-based indices, because the stock market is in some respects more informationally efficient than the private market.) Furthermore, the REIT-based indices reflect idiosyncratic effects of REIT-level management. as well idiosyncratic returns to the REITs' underlying property holdings.[22] Perhaps most interesting is the apparent ability of the REIT-based delevered indices to lead the private market price movements. This can be seen during the months of 2007. For example, the REIT-based Office index begins to decline in January 2007, whereas the Moody's/REAL suggests that prices in the private market did not begin to decline until after the following June.

The difference noticeable in Chart (11) between the REIT-based index and the private market based index in the Apartment sector is logically attributable to the difference in condo conversion participation during this time period, with REITs being less active in this market than private investors. Chart (16) highlights the spike in private-market condo conversions beginning in 2003/2004 and declining by 2007. During 2004-05, condo conversion demand drove up the prices of apartment property transactions in the private market broadly as landlords sold out to converters. But apartment REITs were generally permanently committed to remaining in the apartment rental business, and the stock market knew that. Hence, apartment REIT share prices were not bid up in anticipation of "flipping" apartments to condo-converters. The REIT-based apartment index therefore continued to reflect more fundamental valuations of apartments as rental units, unlike many transactions in the direct private property market. By late 2005 and 2006, the condo boom came to an abrupt end, causing the drop in prices in the private market reflected in the Moody's/REAL index during that period, while the REIT-based valuations continued to rise steadily. The last surge in the private equity and CMBS-based boom in the private market was reflected in the Moody's/REAL Index upsurge from late 2006 through mid-2007, whereas the REIT-based apartment index began its downturn in January 2007, anticipating the subsequent private market correction.

[22] As noted in the previous section, the pureplay methodology endeavors to minimize the idiosyncratic return components in the REIT-based indexes, but there still remains some idiosyncratic component. The Moody's/REAL indexes also reflect some property-level idiosyncratic effects, which would differ from those in the REIT indexes.

Table (1) A Volatility Comparison

	Apt	Office	Indust	Retail	Hotel
REIT-based Monthly Delevered Annualized Volatility	4.80%	5.84%	6.46%	5.18%	10.15%
Moody's/REAL Quarterly Annualized Volatility	8.06%	6.27%	7.05%	5.11%	N/A

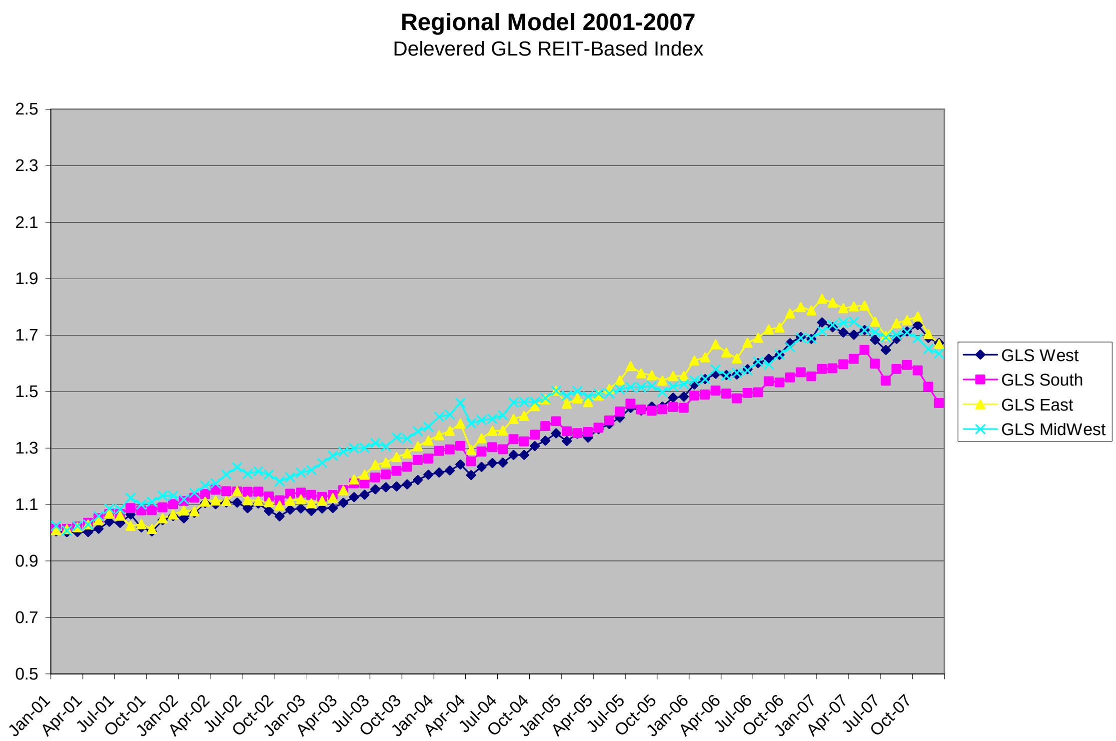
Table (1) compares the annualized volatilities of REIT-based delevered indices with the Moody's/REAL indices over the same period.[23] The volatilities of the regression-based delevered indices are similar to or lower than the volatilities of the corresponding transaction based private market indices.[24]

Using equation (11), we generate property type sector pureplay portfolios. A sample set of such portfolio weights for a single month in 2006 for the office sector is included in appendix table (A1). The largest long positions are highlighted in bold font. The portfolio in table (A1) represents the minimum variance portfolio with a 100% exposure to the target sector and a 0% exposure to other sectors.

[23] Annualized volatility = monthly volatility * sqrt(12) for REIT-based index; quarterly volatility * sqrt(4) for Moody's/REAL index.

[24] NCREIF indexes may have lower volatility, but they are based on appraisals rather than actual transaction prices. With an appraisal-based index, low volatility suggests a concern about lagging and smoothing in the appraisal and index construction process. However, in the case of a transaction based or stock market based index, artificial lagging and smoothing are not a concern, rendering low volatility an indication of a good quality index that avoids excess noise or idiosyncratic variance.

Chart (17)



As noted, the pureplay indexes can be constructed to target geographic regions as well as property usage-type sectors. Based on equation (24), chart (17) shows results for the delevered geographic model. Over the seven year period, the regions displayed similar behaviors, with the Eastern region outperforming the Southern region. In general, there appears to be greater price movement dispersion across usage-type sectors within regions than across regions within property-type sectors.

Turning now to the more granular indices of regional usage-type sectoral returns, we subdivide each property type sector into four regional market segments, yielding a total of twenty explanatory variables as described on page 10. However, the inclusion of twenty explanatory variables causes excessive standard errors in the estimated segment returns due to the multicollinearity of a few of the exposure variables.[25] In order to quantify and mitigate the severity of this multicollinearity, we calculate variance inflation factors (VIFs)[26].

The VIF is derived from the equation for the variance of the regression coefficients:

---

[25] Fundamentally, this is due to insufficient REIT holdings in the case of the Hotel sector. In the Industrial sector, the multicollinearity is caused not by a scarcity of holdings but rather by similar investment patterns across REITs.

[26] For a presentation on Variance Inflation Factors, see, for example, Greene's Econometric Analysis Fifth Edition., pg. 56-58.

$$VAR(b_k) = \frac{\sigma^2}{\left(1 - R_k^2\right)\sum_{i=1}^{N}\left(x_{i,k} - \bar{x}_k\right)^2} \tag{26}$$

where R_k^2 is the R-squared from the regression of explanatory variable *k* on all explanatory variables excluding variable *k*. It is evident that as R_k^2 gets larger, the variance of the estimated regression coefficient becomes larger. In the case of perfect collinearity, R_k^2=1 and the variance of the estimated regression coefficient is infinite. VIF is defined as:

$$VIF_k = \frac{1}{\left(1 - R_k^2\right)} \tag{27}$$

Thus,VIF captures the relationship between the collinearity of an explanatory variable and the resulting increase in variance of the estimated coefficient for the variable. The square root of the VIF, labeled "Factor" in Table (2), measures how many times higher the standard error of the regression coefficient is as a result of collinearity. A factor equal to one implies that there is no collinearity for explanatory variable *k*; the standard errors are not inflated (variable *k* is orthogonal). A factor equal to two implies that the standard errors for coefficient *k* are twice as high as they would be if variable *k* was orthogonal.

Table (2)

20-Segment Model			16-Segment Model		
Variable	**VIF**	**Factor**	**Variable**	**VIF**	**Factor**
Apartment East	1.31	1.15	Apartment East	1.31	1.15
Apartment Midwest	1.22	1.11	Apartment Midwest	1.22	1.11
Apartment South	1.32	1.15	Apartment South	1.31	1.15
Apartment West	1.14	1.07	Apartment West	1.14	1.07
Hotel East	**3.95**	1.99	Hotel Combined	1.00	1.00
Hotel Midwest	**10.58**	3.25			
Hotel South	**10.73**	3.28			
Hotel West	**2.70**	1.64			
Industrial East	1.68	1.30	Industrial East	1.62	1.27
Industrial Midwest	**2.36**	1.54	Industrial Midwest	**2.27**	1.51
Industrial South	**4.26**	2.06	Industrial South+West	1.67	1.29
Industrial West	**4.16**	2.04			
Office East	1.25	1.12	Office East	1.23	1.11
Office Midwest	1.69	1.30	Office Midwest	1.58	1.26
Office South	1.63	1.28	Office South	1.63	1.28
Office West	1.22	1.11	Office West	1.11	1.05
Retail East	1.22	1.10	Retail East	1.22	1.10
Retail Midwest	1.34	1.16	Retail Midwest	1.34	1.16
Retail South	1.27	1.13	Retail South	1.25	1.12
Retail West	1.42	1.19	Retail West	1.42	1.19

For each month over the period 2001-2007, we regress each market segment variable on all remaining market segment variables and calculate VIFs. We average the 84 period VIFs to get the average VIFs reported in the table above. High VIFs are in bold type.

Using this data, along with simple correlations between independent variables, we combine the hotel market segments into a single combined independent variable. We also combine Industrial South and Industrial West. The resulting VIFs in the 16-segment model are much lower for the combined segments and mostly unchanged for the remaining segments. Only the Industrial Midwest segment remains possibly problematical. It is important to remark that the VIFs for the regional Hotel market segments drop significantly between 2001 and 2007. In fact, by 2006, the regional Hotel VIFs are all 2.00 or lower as a result of increased REIT participation in the Hotel market segment. In the future, it may be desirable to disaggregate the Hotel segments. In contrast, the VIFs for Southern Industrials and Western Industrials remain stable over the period. Given the limitations of the data, we are unable to explore market segments such as economic/metropolitan regions. However, our early investigations suggest that with additional data, further segmentation will be possible and valuable.

Charts (18)-(21) show for each of the four main property sectors (apartment, office, industrial, retail) the graphs for the delevered 16-segment model alongside the corresponding Moody's/REAL CPPI Indices (where available) and the national sector index previously reported in charts (11)-(15). The Hotel index is not presented again here as the results are essentially unchanged from Chart (15).

Chart (18)

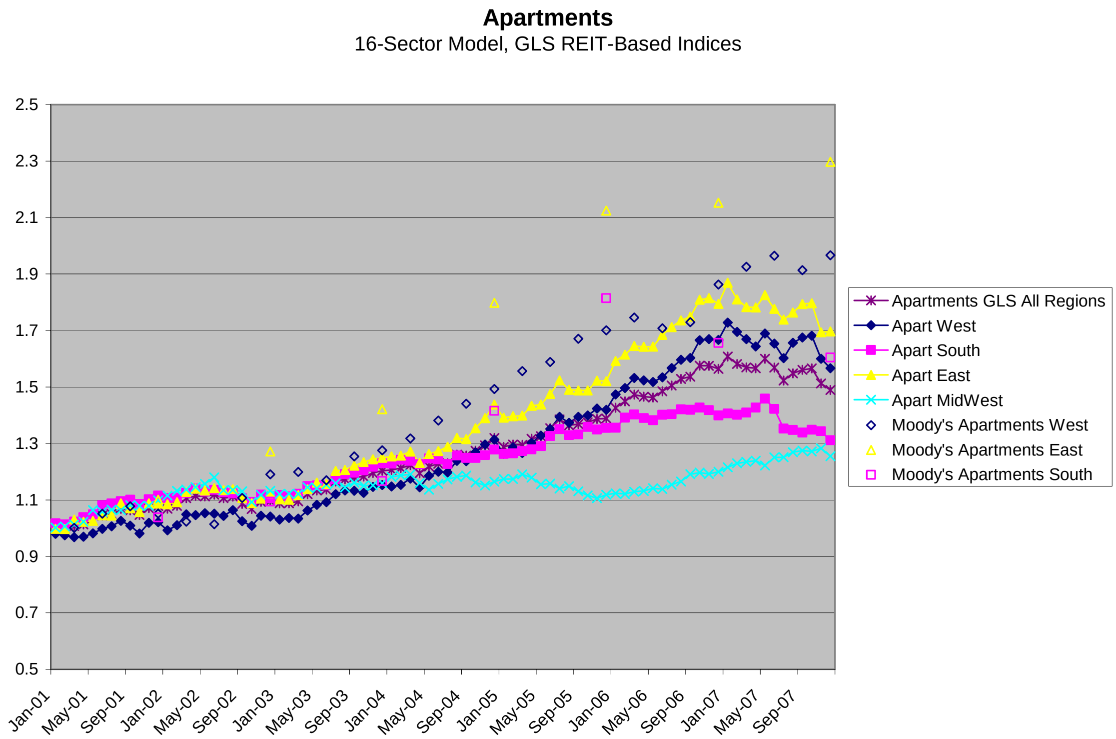
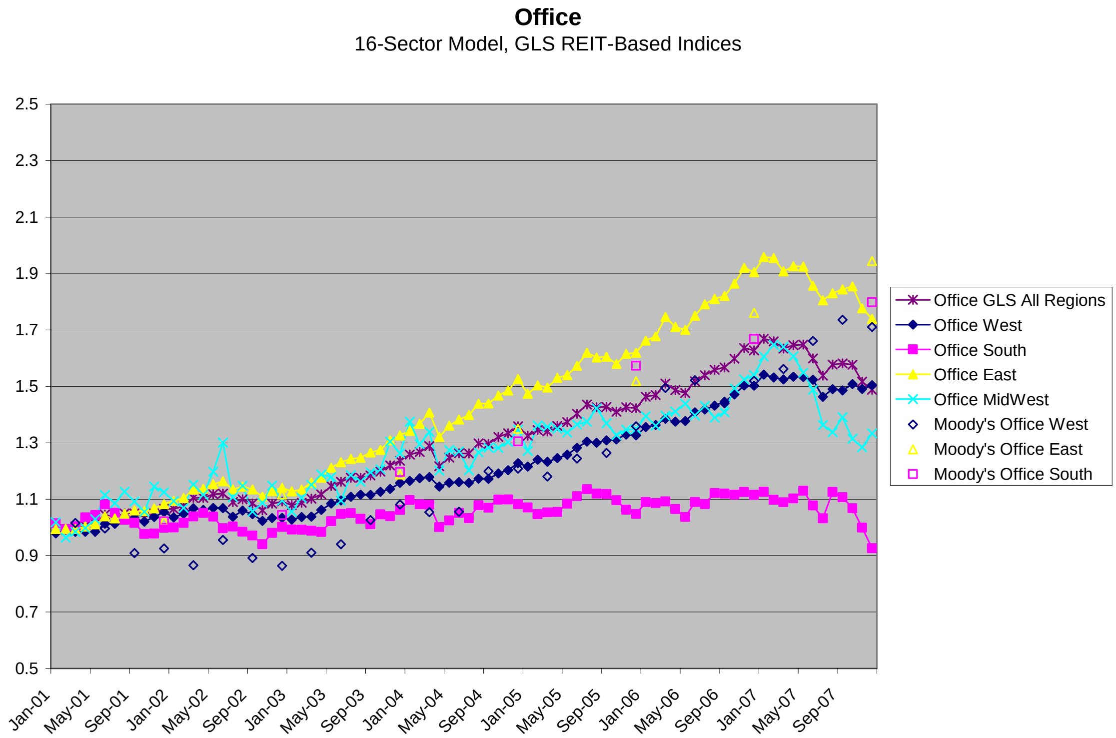
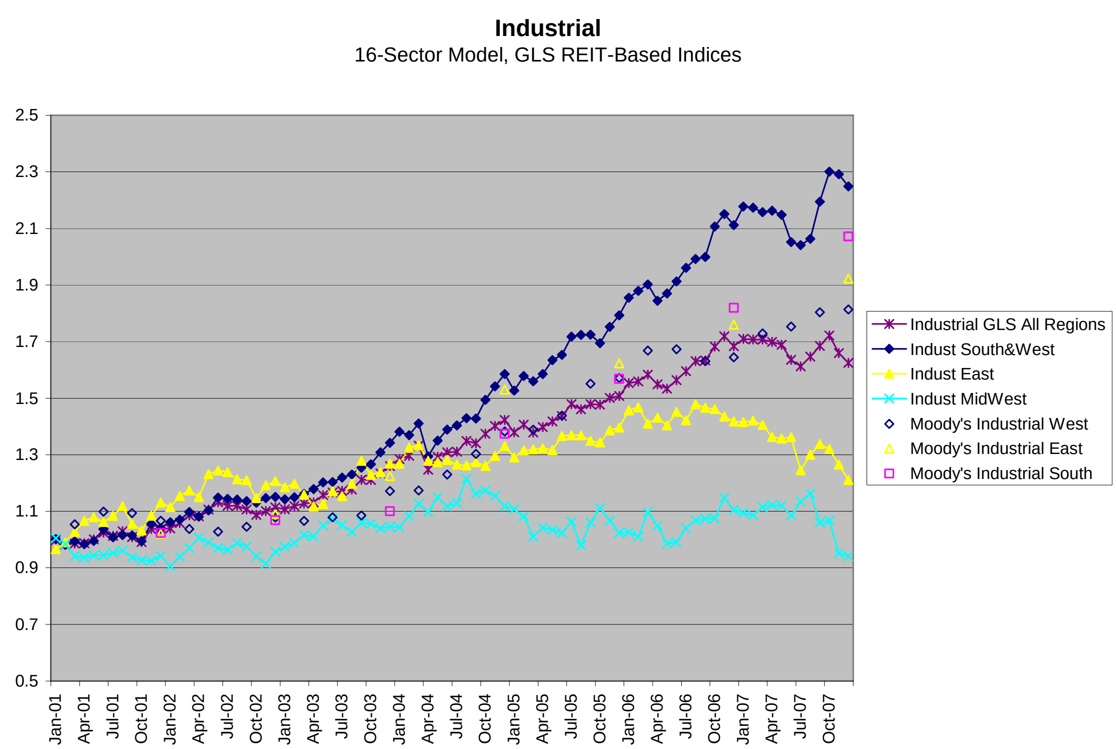


Chart (19)


Office
16-Sector Model, GLS REIT-Based Indices
2.5
2.3
2.1
1.9
1.7
1.5
1.3
1.1
0.9
0.7
0.5
Jan-01
May-01
Sep-01
Jan-02
May-02
Sep-02
Jan-03
May-03
Sep-03
Jan-04
May-04
Sep-04
Jan-05
May-05
Sep-05
Jan-06
May-06
Sep-06
Jan-07
May-07
Sep-07
Office GLS All Regions
Office West
Office South
Office East
Office MidWest
Moody's Office West
Moody's Office East
Moody's Office South


Industrial
16-Sector Model, GLS REIT-Based Indices
2.5
2.3
2.1
1.9
1.7
1.5
1.3
1.1
0.9
0.7
0.5
Jan-01
Apr-01
Jul-01
Oct-01
Jan-02
Apr-02
Jul-02
Oct-02
Jan-03
Apr-03
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Jan-04
Apr-04
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Jan-05
Apr-05
Jul-05
Oct-05
Jan-06
Apr-06
Jul-06
Oct-06
Jan-07
Apr-07
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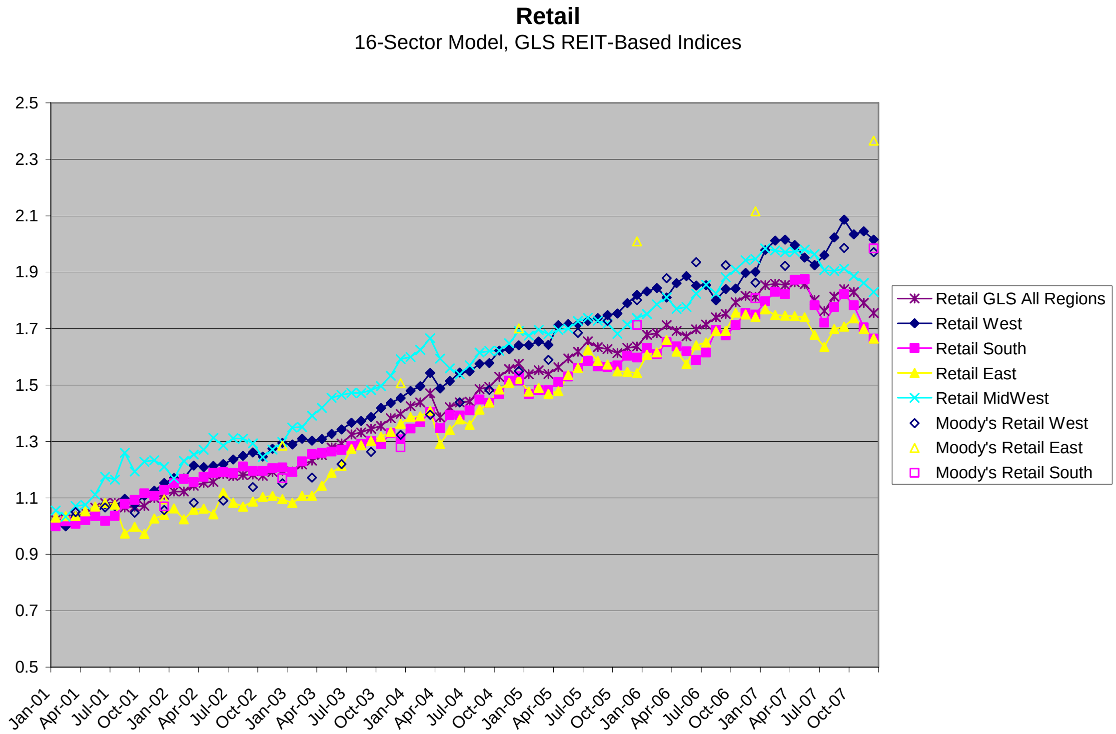
Industrial GLS All Regions
Indust South&West
Indust East
Indust MidWest
Moody's Industrial West
Moody's Industrial East
Moody's Industrial South



Although generally there is a greater divergence in performance across sectors within regions than across regions within sectors, nevertheless there are some differences in regional performance within the property-type sectors. The difference in cumulative return performance between Southern/Western industrials and Midwestern Industrials is over 130%. There is less regional differentiation within the retail sector, with the West Coast outperforming the East Coast by 35%. The Moody's/REAL does not reflect as much regional differentiation as our regression-based REIT indices.

Finally, beginning in 2004, we generate the national sector indices on a daily basis. We have not yet been able to update property portfolio holdings or balance sheet data on a daily basis for this study, but we observe little change in overall proportional holdings, even on a quarterly basis. Daily returns for REITs are readily available. Charts (22)-(26) show the estimated indices for each industry segment on a daily basis and on a monthly basis. The charts also show the quarterly Moody's/REAL CPPI.

We wish to highlight two striking observations. First, as described previously at the monthly frequency, the REIT-based indices appear to lead the Moody's/REAL CPPI, as can be seen most clearly in the Office Sector graph. Second, increasing the estimation frequency from monthly to daily does not introduce additional noise to the estimated indices. This is confirmed visually by the graphical comparison of the daily and monthly indices, and statistically in table (3) which provides a comparison of volatilities of the indices.

Chart (22)

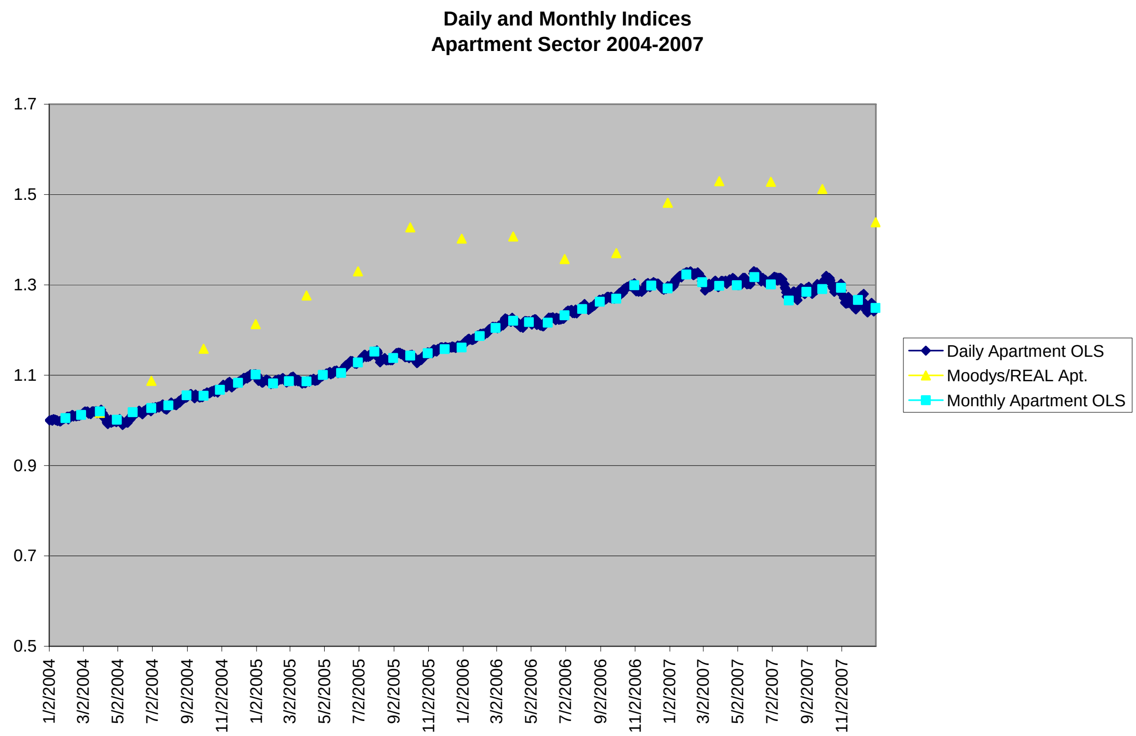


Chart (23)

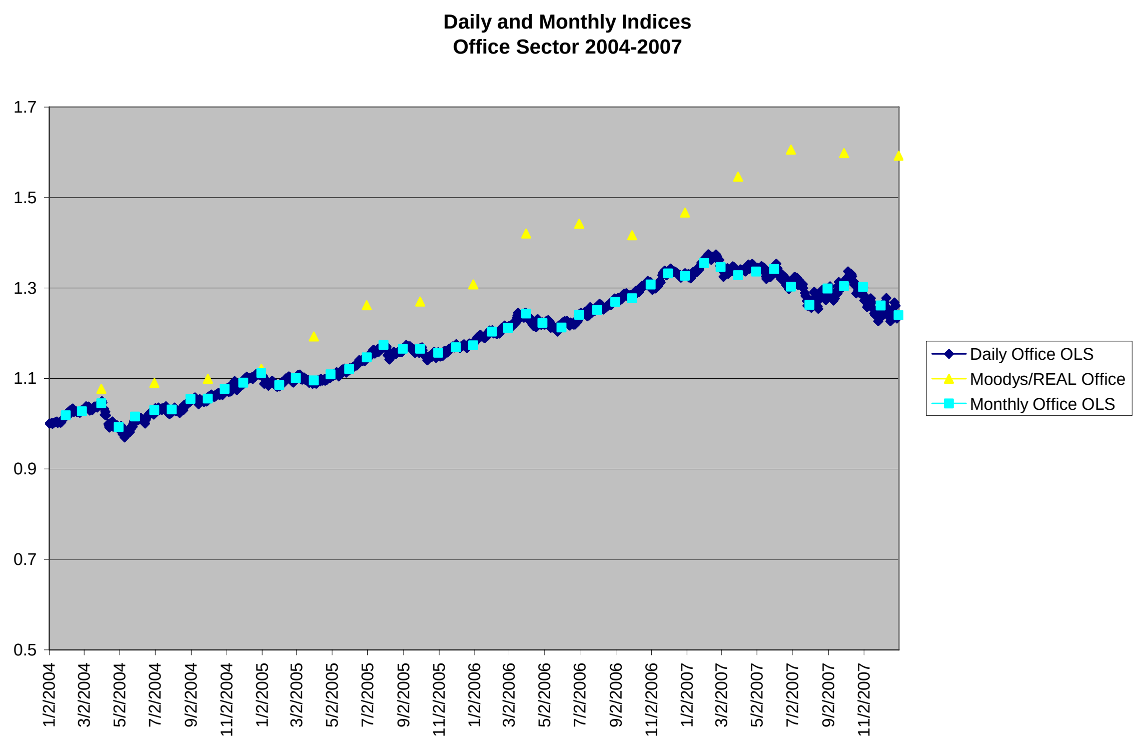


Chart (24)

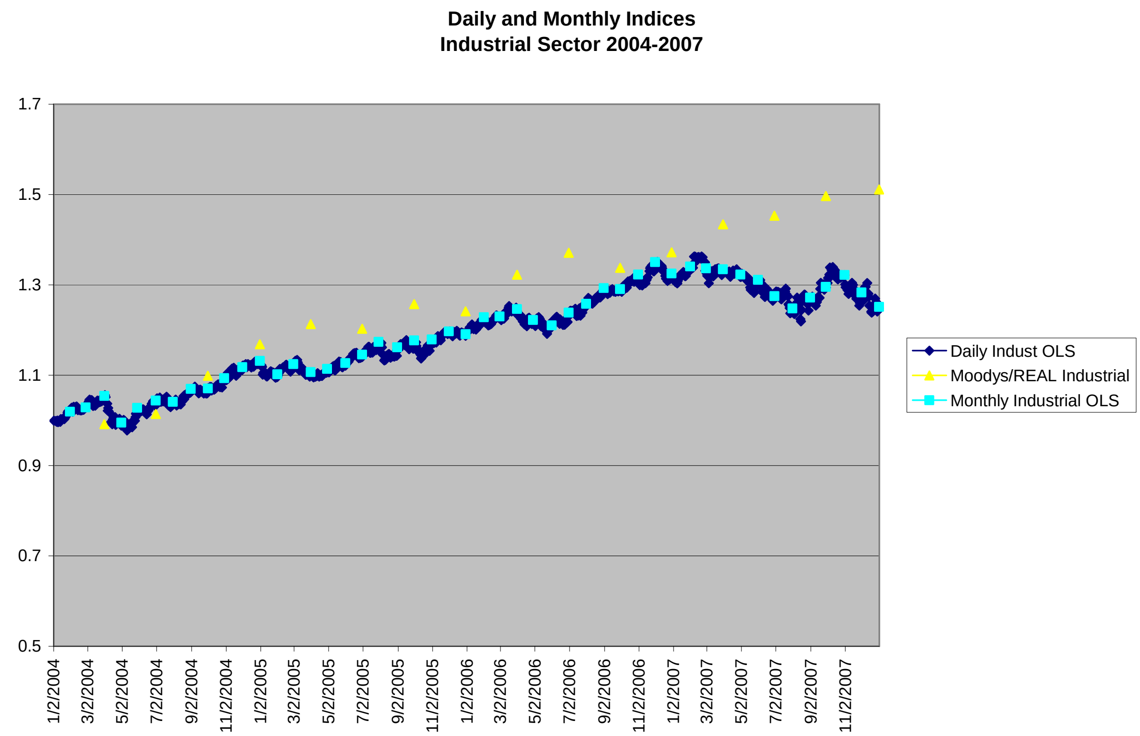


Chart (25)

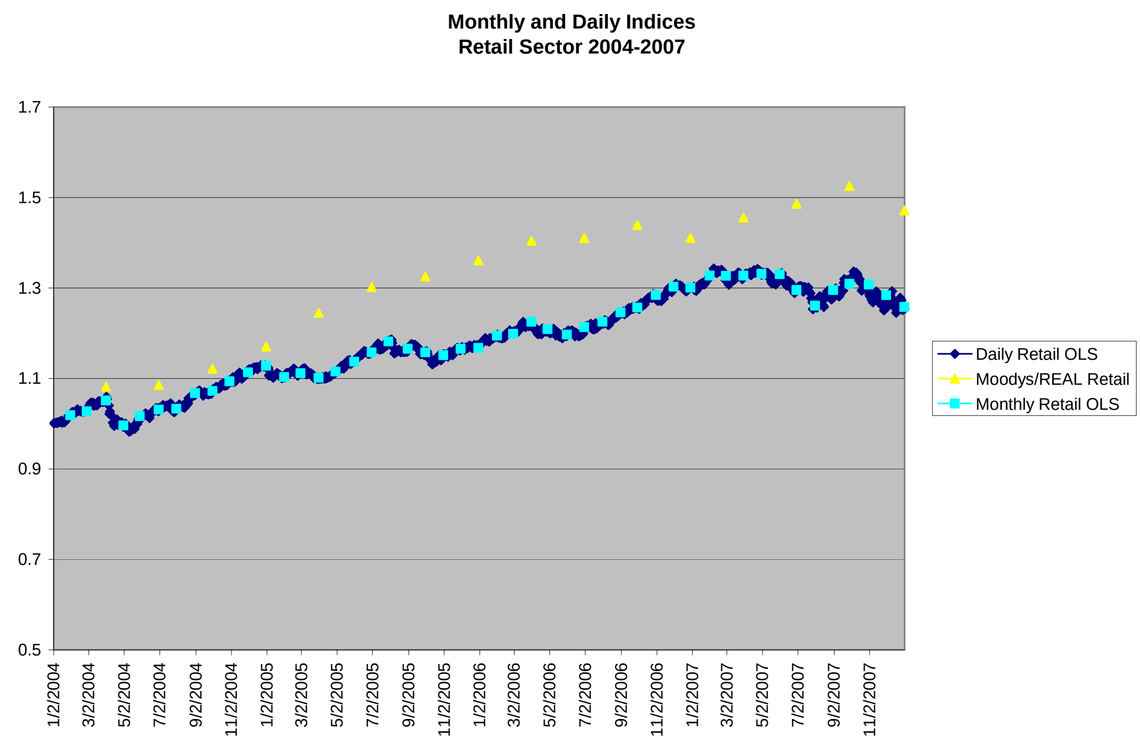


Chart (26)

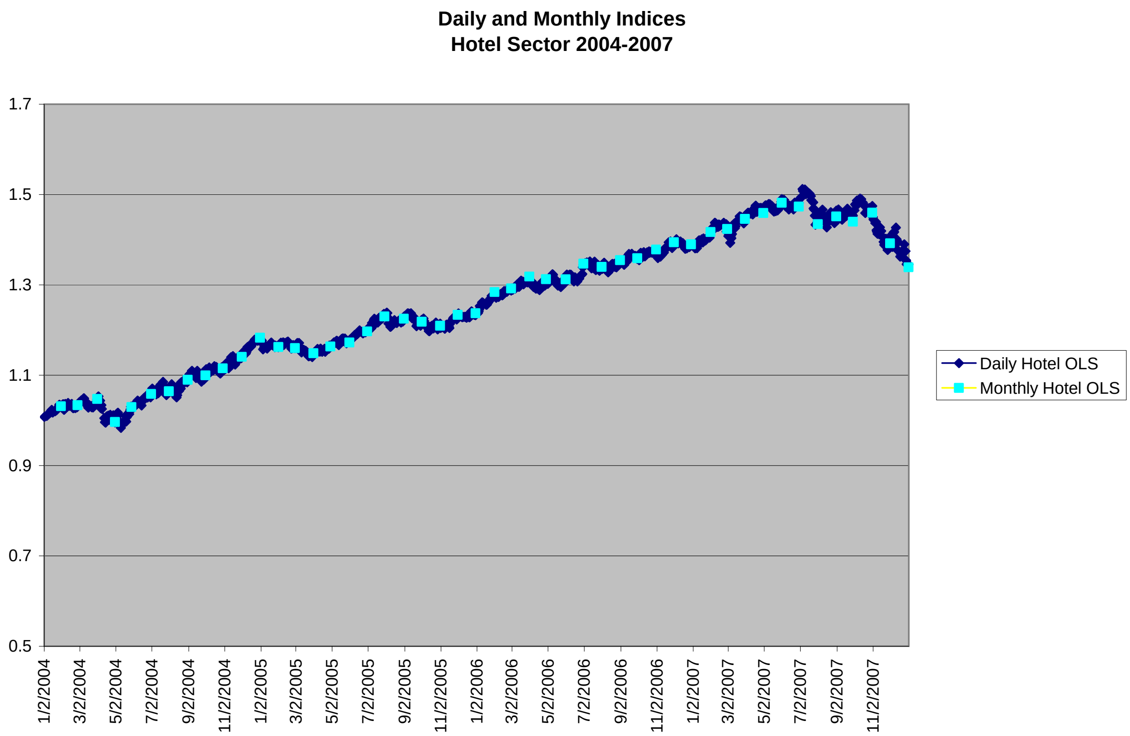


Table (3) Volatility Comparison

	Apart.	Office	Indust.	Retail	Hotel
Daily Model Annualized Volat.	4.70%	6.49%	6.25%	6.32%	7.34%
Monthly Model Annualized Volat.	4.36%	6.11%	6.18%	6.27%	7.27%
Moody's/REAL CPPI Quarterly Annualized Volat.	8.03%	6.15%	6.13%	5.70%	N/A

The Role of Pureplays in the Real Estate Investment Strategy

The pureplay portfolios presented here are of interest as information tools, to empirically track price movements and investment returns in property market segments. However, they potentially go beyond merely providing useful information to the marketplace. These indexes present interesting possibilities for supporting derivatives and investment vehicles for synthetic or indirect investment in commercial property. Recently, trading of derivatives based on private market indexes of commercial property returns has significantly taken off in the UK, where the notional value of swaps traded based on the (appraisal-based) IPD Index has recently grown to approximately one-half the cash trading volume in the physical properties tracked by the index.[27] Synthetic real estate investment vehicles offer advantages over traditional direct-property investing for certain types of investors, as they can provide lower transactions and management costs, less management burden, greater diversification across individual properties, and the ability to sell short (which enables hedging of real estate market risk exposures).

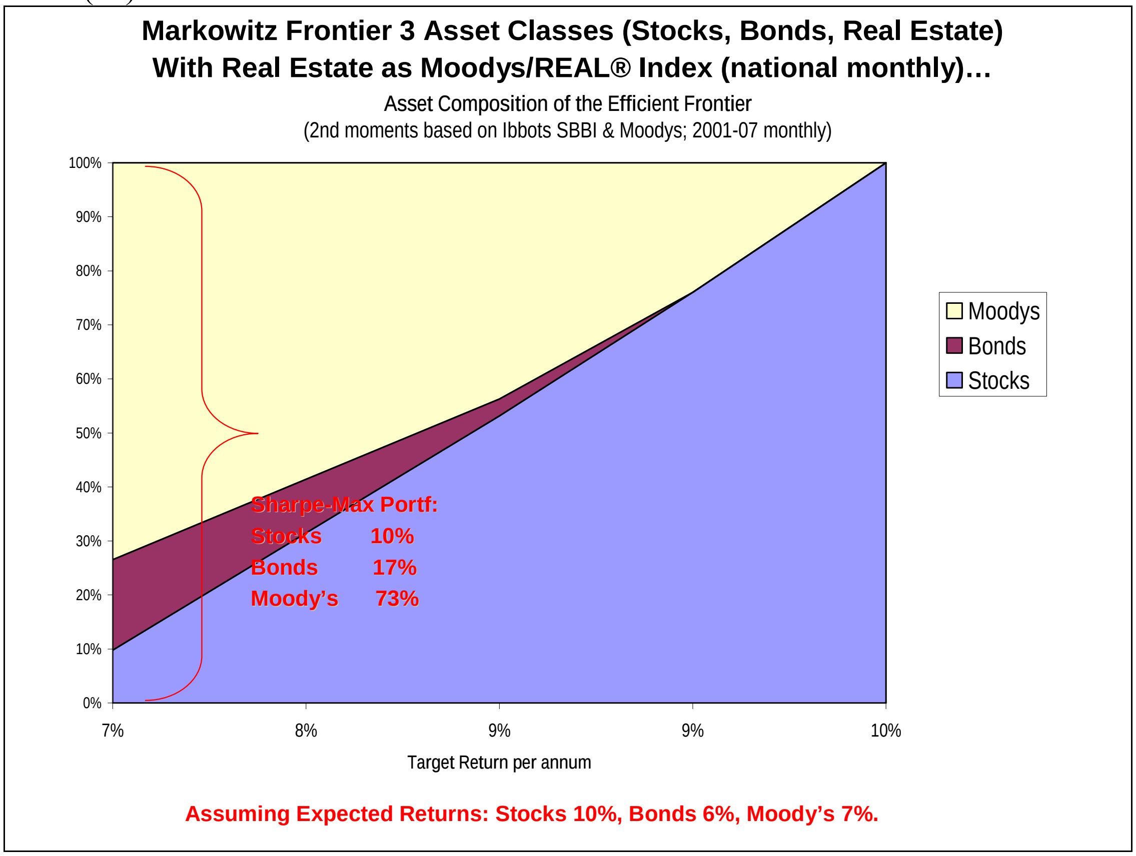
The pureplay indexes presented in this paper offer several advantages as a tool to support commercial property derivatives and synthetic or indirect property investment. First, as we have seen, the public market tends to lead the private market in time, so the pureplay indexes reflect the relevant price discovery in each property market segment. Second, the pureplay indexes can be produced at high frequency without loss of accuracy. For example, daily-updated indexes can easily be produced based on daily REIT share closing prices. Frequent updating can be very useful in derivatives markets as it allows frequent marking-to-market of the values of the derivative contracts, which in turn minimizes required margin positions. Third, unlike private market based indexes where it is not possible to actually buy and sell the underlying properties, the pureplay portfolios can in principle be directly constructed and traded via long and short positions taken in the publicly-traded REITs that compose the portfolios. This facilitates pricing of derivatives (as it renders more meaningful the use of traditional arbitrage-based pricing formulae), and it also enables construction of exchange-traded funds (ETFs) that track or implement the pureplay indexes. This facilitates the "counter-party problem" which can make it difficult to get a liquid derivatives market established.

To gain some insight into the role that the pureplay indexes presented in this paper could play in overall investment strategy, we have performed a simple optimal mean-variance portfolio allocation analysis considering three aggregate-level asset classes: stocks, bonds and real estate, with real estate represented three alternative ways: (i) by investment in the private property market as represented by the Moody's/REAL transactions-price-based index; (ii) by investment in REITs as represented by the NAREIT equity-REIT index; and (iii) by investment in the pureplay portfolios presented here as represented by an equally-weighted combination of the four major national property sectors. The stock and bond returns are represented by Ibbotson Associates (SBBI) indices of the S&P500 and long-term Treasury Bonds. In all cases the second moments (asset class volatilities and correlations across the asset classes) are based on the historical monthly statistics from the 2001-07 period covered in this paper. The total return expectations (mean returns) for each asset class are based on the authors' judgments about likely equilibrium expectations, in particular: 10% for the stock market, 6% for the bond market, 7% for unlevered real estate (Moody's and pureplays), and 10% for REITs (as the NAREIT index is effectively levered).[28] The results are shown in charts (27)-(29).

[27] In the U.S., trading on the NCREIF Index has been slower to take off, but has been active since mid-2007, with over $1 billion notional value of NPI swaps traded over-the-counter by late 2008. (This is still miniscule compared to cash trading in commercial property exceeding $300 billion in the U.S. during 2006, as tracked by Real Capital Analytics.)

[28] All returns *per annum*. Historically, REIT returns have averaged approximately the same as the S&P500, even though REIT betas average significantly less than unity. However, REIT betas tend to be higher in

Chart (27)



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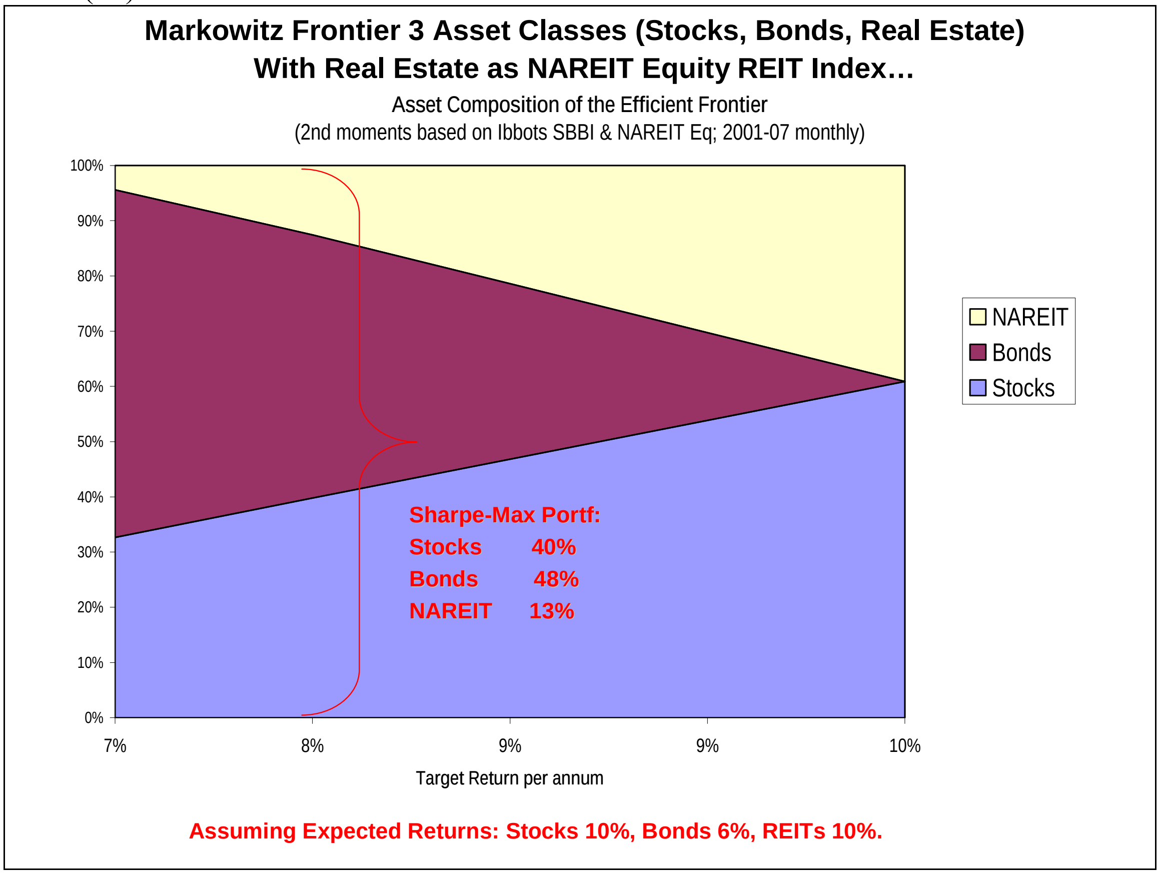
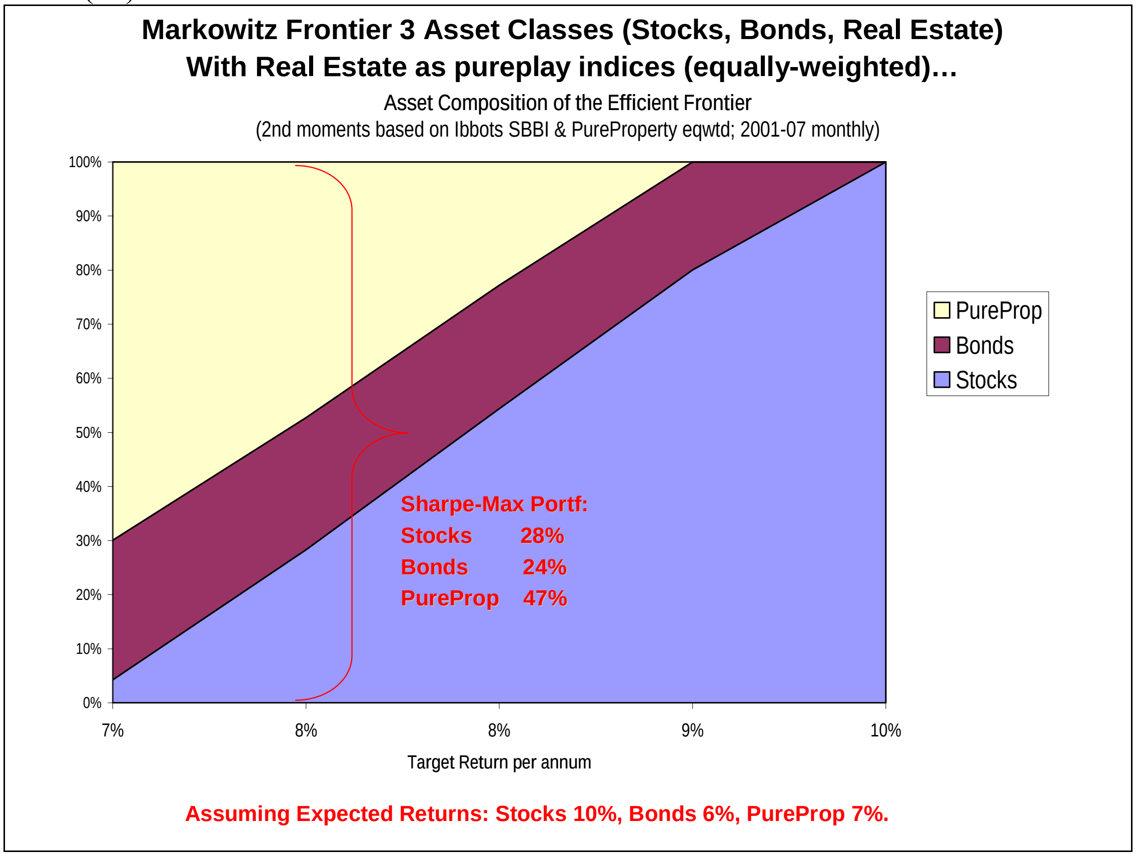
down-markets, and most REITs are relatively low-growth, small to medium size firms, which tend to give them positive "Fama-French" factor expected return premiums.

Chart (28)



Markowitz Frontier 3 Asset Classes (Stocks, Bonds, Real Estate)
With Real Estate as NAREIT Equity REIT Index…
Asset Composition of the Efficient Frontier
(2nd moments based on Ibbots SBBI & NAREIT Eq; 2001-07 monthly)
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
7%
8%
9%
9%
10%
Target Return per annum
NAREIT
Bonds
Stocks
Sharpe-Max Portf:
Stocks 40%
Bonds 48%
NAREIT 13%
Assuming Expected Returns: Stocks 10%, Bonds 6%, REITs 10%.

Chart (29)


Markowitz Frontier 3 Asset Classes (Stocks, Bonds, Real Estate)
With Real Estate as pureplay indices (equally-weighted)…
Asset Composition of the Efficient Frontier
(2nd moments based on Ibbots SBBI & PureProperty eqwtd; 2001-07 monthly)
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
7%
8%
8%
9%
10%
Target Return per annum
PureProp
Bonds
Stocks
Sharpe-Max Portf:
Stocks 28%
Bonds 24%
PureProp 47%
Assuming Expected Returns: Stocks 10%, Bonds 6%, PureProp 7%.

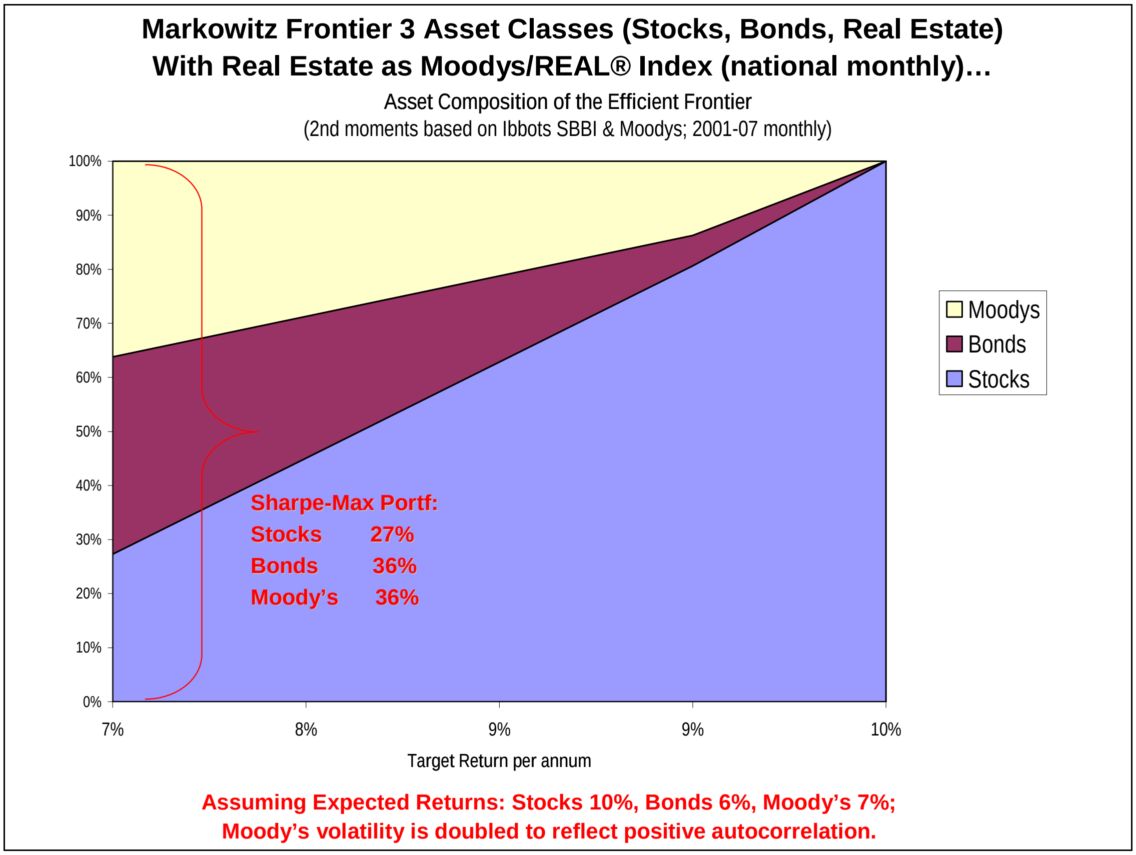
The charts represent Markowitz efficient (non-dominated) portfolios (allocation percentages) of the three asset classes as a function of the target return rates on the horizontal axis. Thus, portfolios farther to the left are more conservative. Note in Chart (27) that if real estate is represented by direct investment in the private market, then real estate is the dominant asset class among the three, with its largest allocation for conservative portfolios. Real estate also dominates in the Sharpe-maximizing portfolio (the portfolio with the greatest Sharpe Ratio, the one that would be the "market portfolio" in a CAPM world where a riskless asset exists). If instead of private market real estate, one substitutes REITs as the representative of the real estate asset class in the portfolio, chart (28) reveals that a very different pattern emerges. Real estate now becomes more prominent in the more aggressive, risk-tolerant portfolios, and its presence in the Sharpe-maximizing portfolio is diminished to only 13%. However, chart (29) reveals that the real estate investment based on the pureplay portfolios presented here assumes a role in the optimal mixed-asset portfolio much more like that of direct private market real estate, skewed toward conservative portfolios and including a large (47%) share of the Sharpe-maximum portfolio.

Furthermore, private market real estate as represented by the Moody's/REAL indices display significant inertia in price movements, with much greater positive autocorrelation in returns than do REIT-based measures such as the pureplay portfolios. This causes longer-term volatility to be greater in private market investment, relative to REIT-based investment.[29] Chart (30) below, shows the efficient frontier if we assume that price movement inertia effectively doubles the volatility in the private real estate market.

The overall suggestion from Charts (27)-(30) is that, from an investment strategy perspective, REIT-based pureplay portfolios can play a role much like private real estate market investment, a rather different role than traditional direct REIT-based investment. Yet as noted at the outset of this section, the REIT-based pureplay portfolios have some basic advantages for constructing derivatives and synthetic investment and hedging vehicles, including ability for daily updating and tradability of the underlying portfolio.

[29] In effect, variance accumulates at a greater than linear rate in private markets, causing relatively large amplitude cyclical market behavior, as contrasted with public exchange markets which tend to follow paths more like a random walk.

Chart (30)



Conclusions

Using REIT return data, property holdings data, and REIT financial information, it is possible to construct REIT-based pureplay indexes (or portfolios) with unit exposure to a desired property market segment, zero exposure to all other property market segments, and minimum idiosyncratic risk. Additionally, with financial data about REIT debt and equity holdings along with information about the cost of REIT debt, it is possible to adjust for REIT leverage and to generate estimated market segment returns for the underlying property market using the segment portfolio weights. These estimated market segment returns, or indices, provide new and valuable information about the underlying property markets on a high-frequency, temporally-leading basis. In this paper, we demonstrate by comparison to the Moody's/REAL indices that a 16-segment model provides good granularity with high frequency potential.

While not the subject of the present paper, it is interesting to note that an important potential contribution of the type of indexes described herein lies in their application to support derivative trading and synthetic investment in the commercial property market. Higher-frequency indices enable lower margin requirements for derivative products such as swaps. Because REIT-based indices lead private-market based indices, they are a more natural basis for derivate products. The tradeable underlying market segment portfolios enable arbitrage execution between the derivative and the underlying, facilitating pricing in the derivative market, providing profit opportunity for traders, and therefore promoting liquidity in the derivatives market. Furthermore, starting from the market segment portfolio weights, sophisticated users can synthetically add or subtract leverage as desired.

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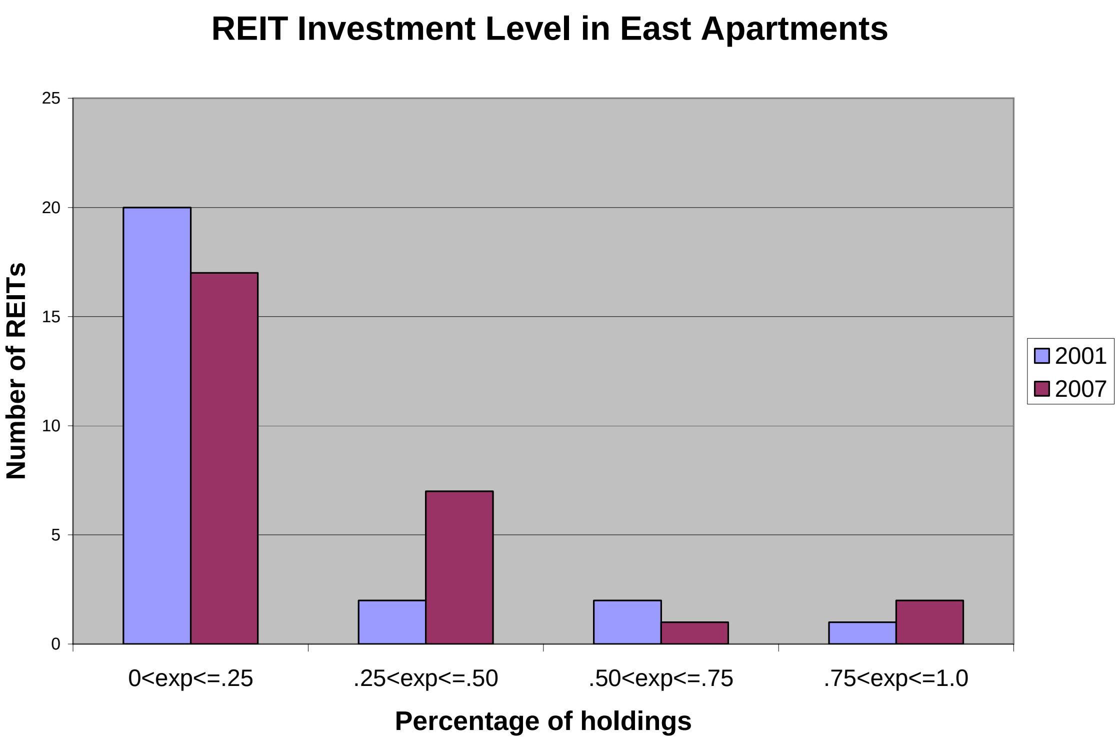
Appendix

Chart (A1)



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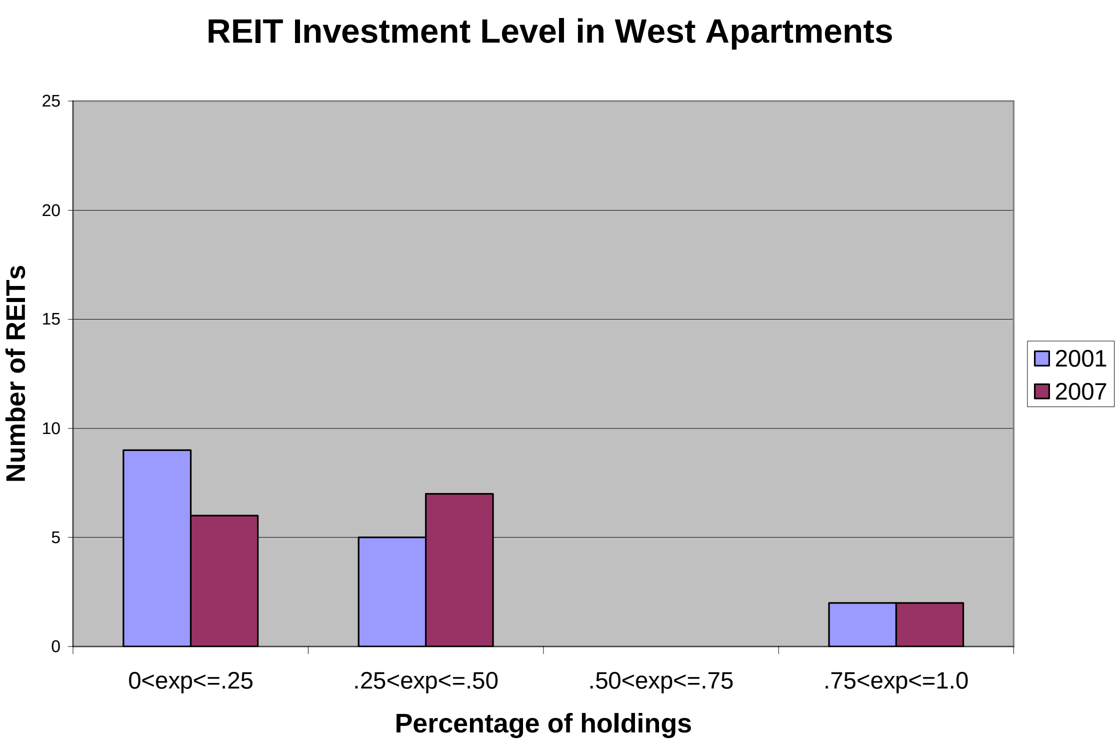

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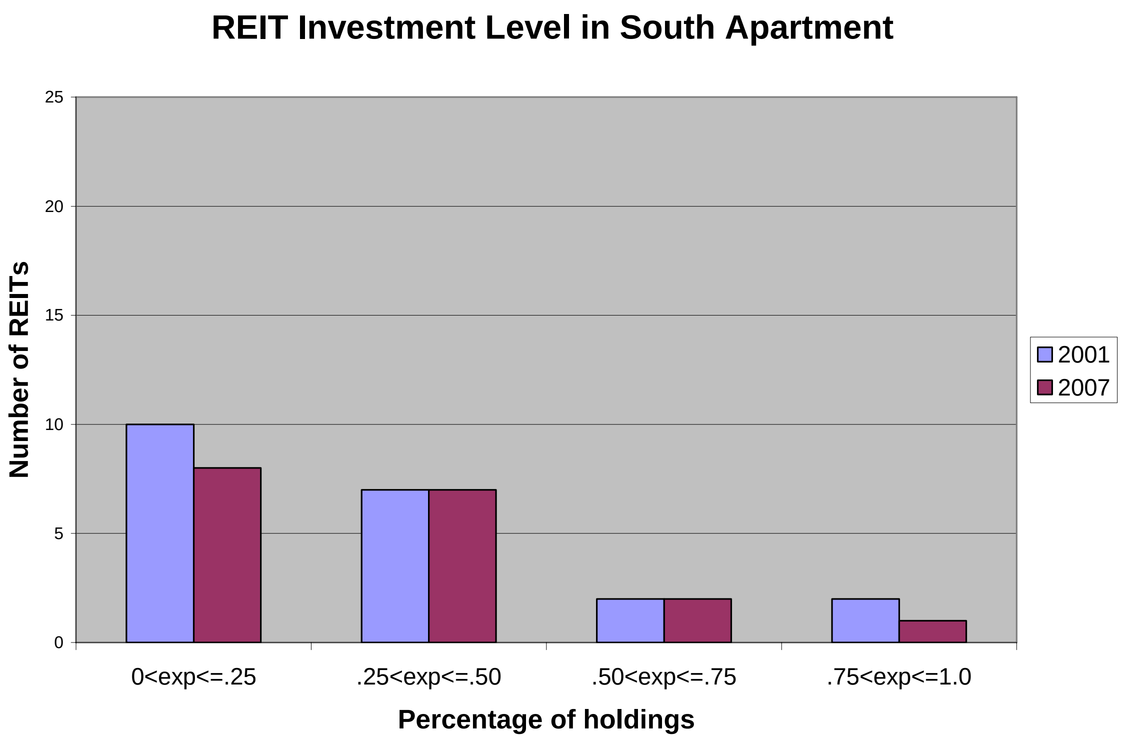

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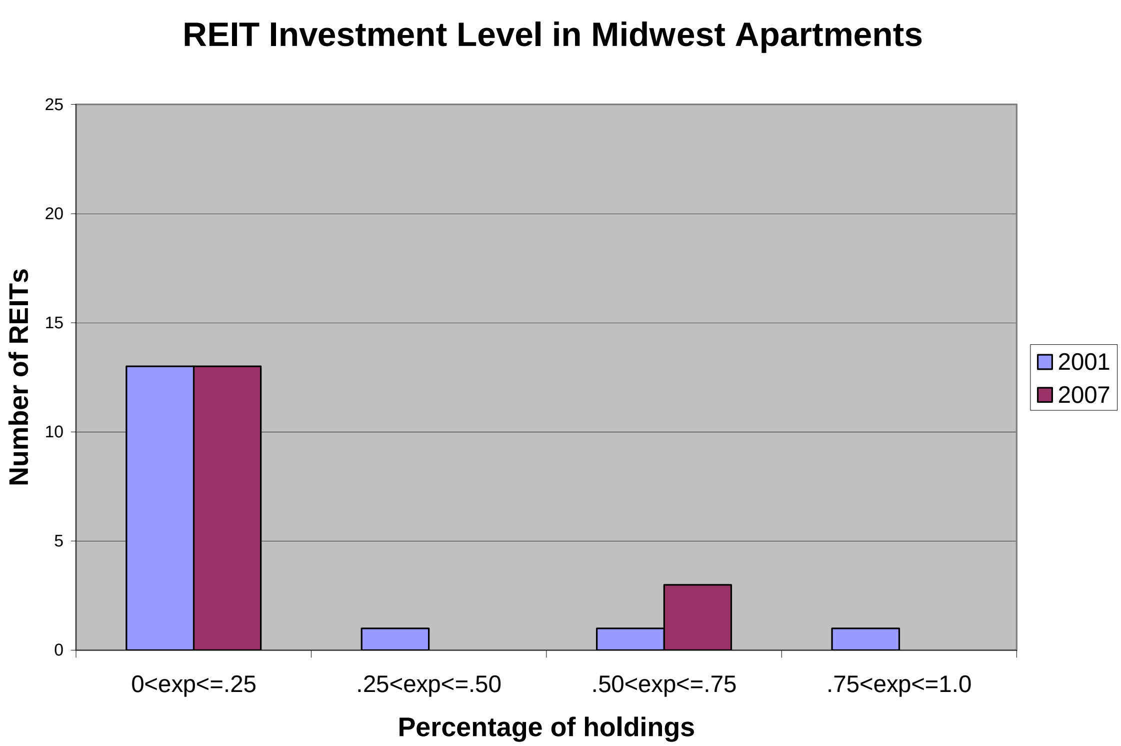

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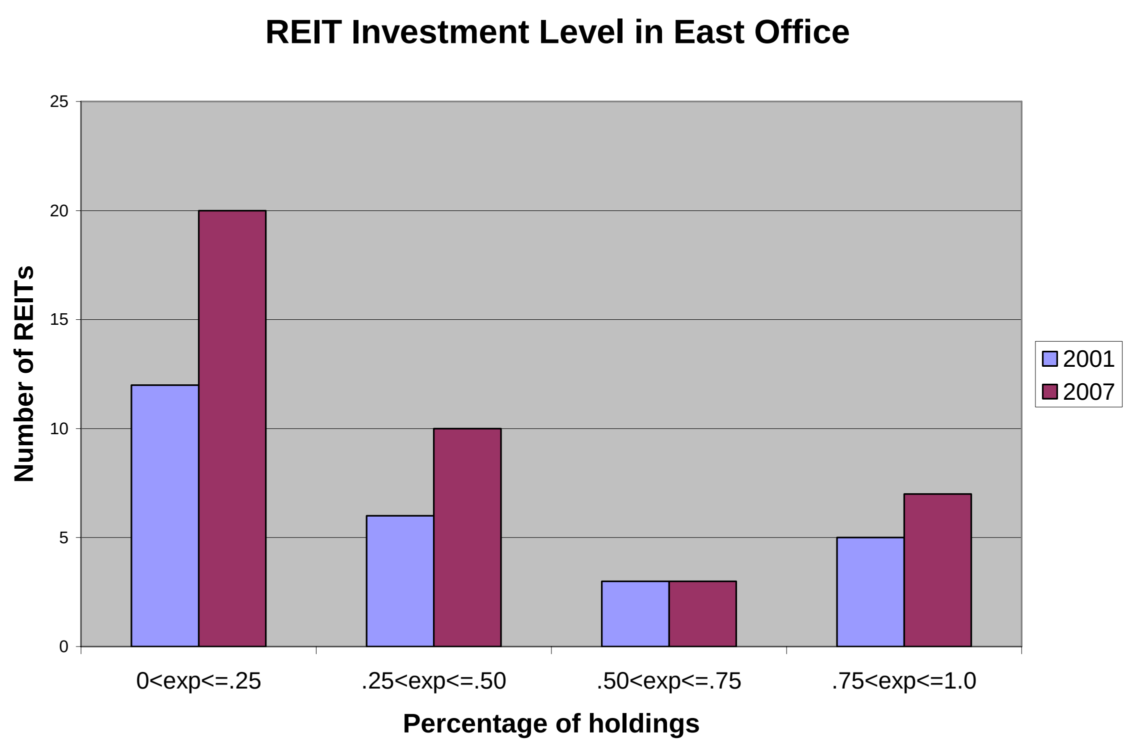

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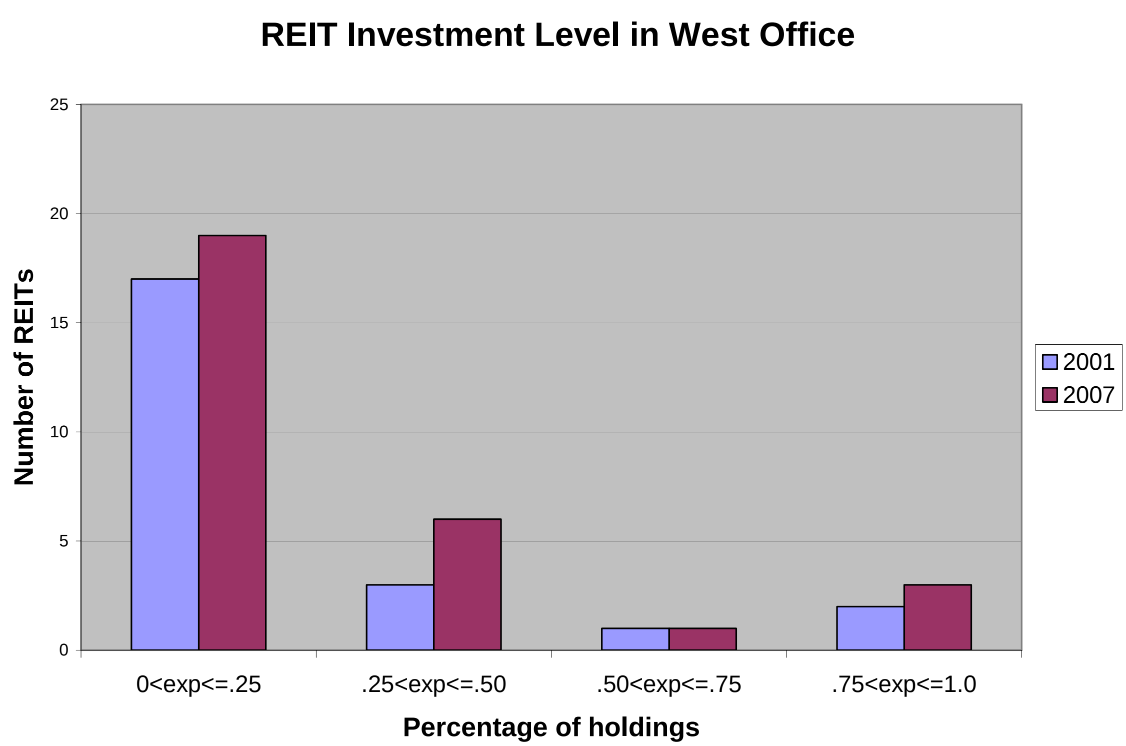

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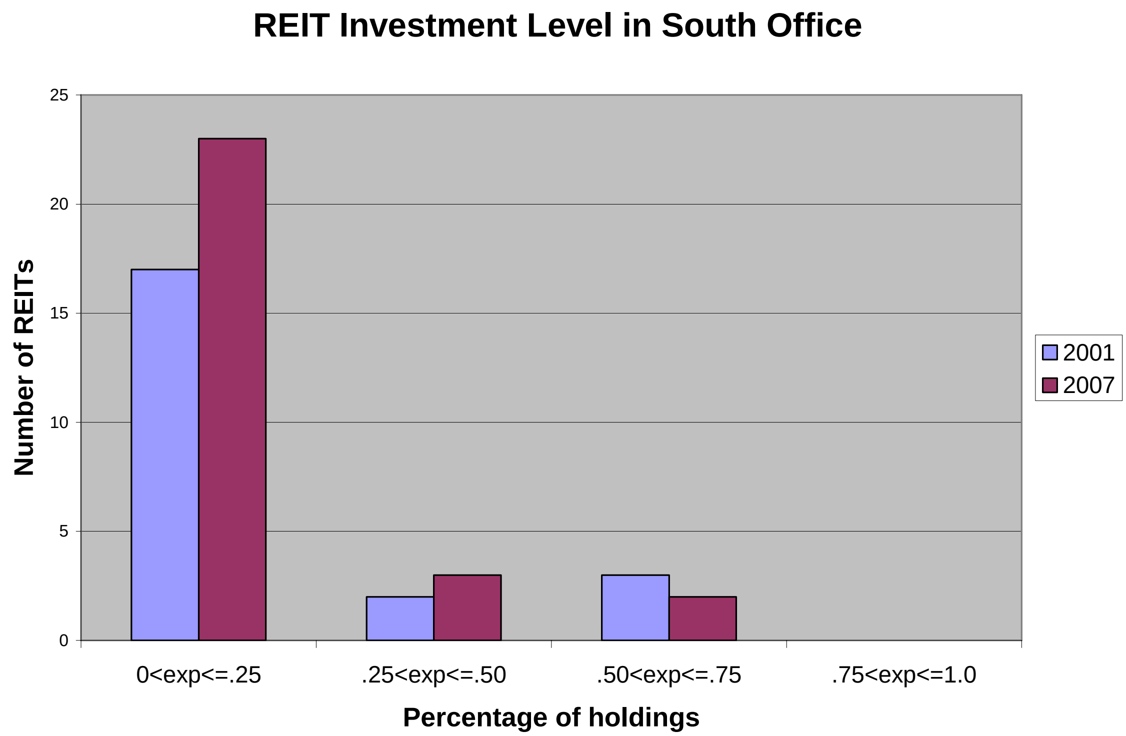

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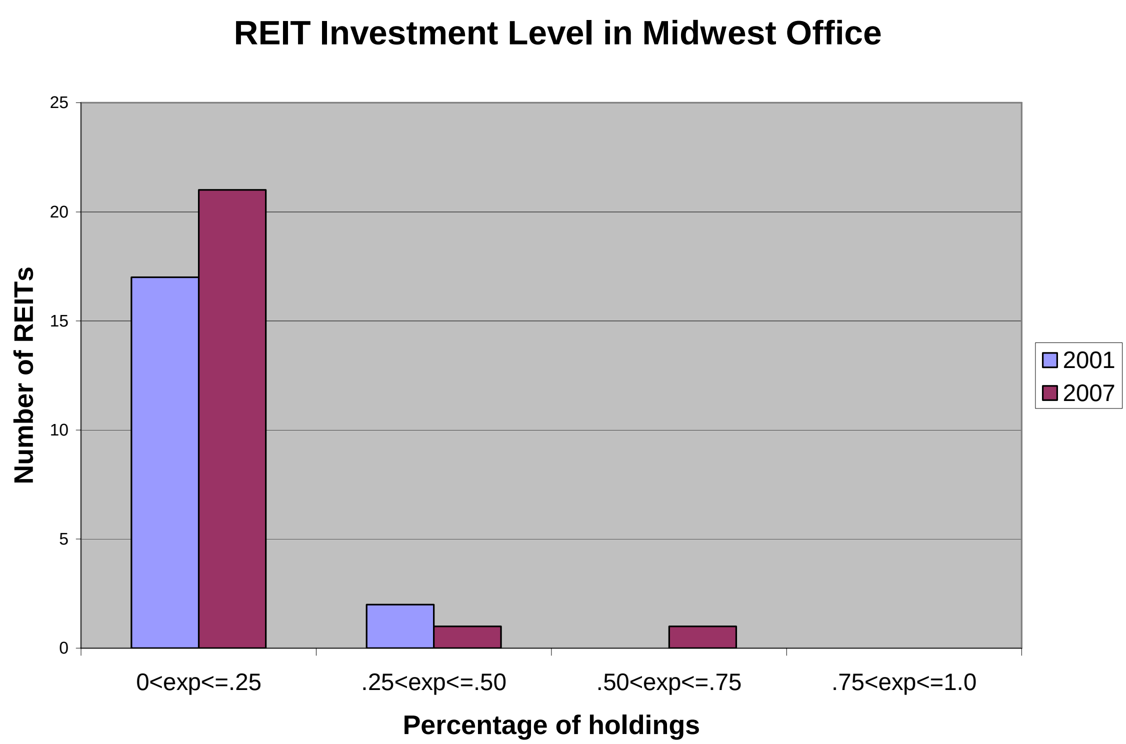

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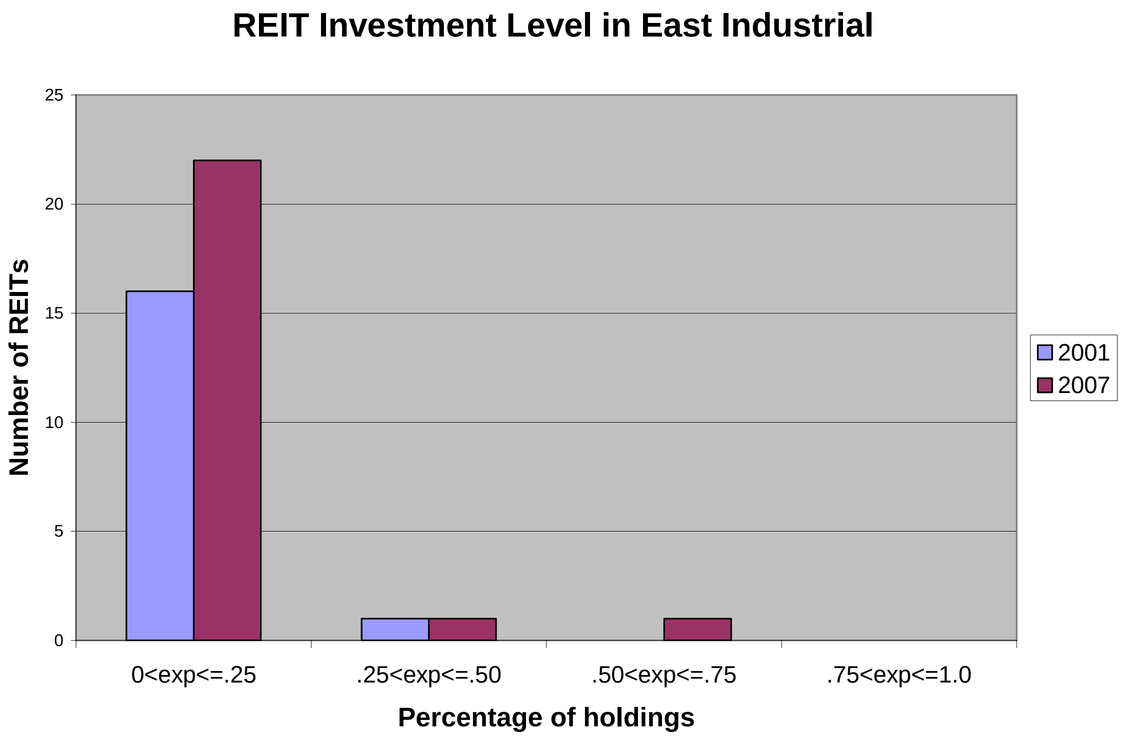

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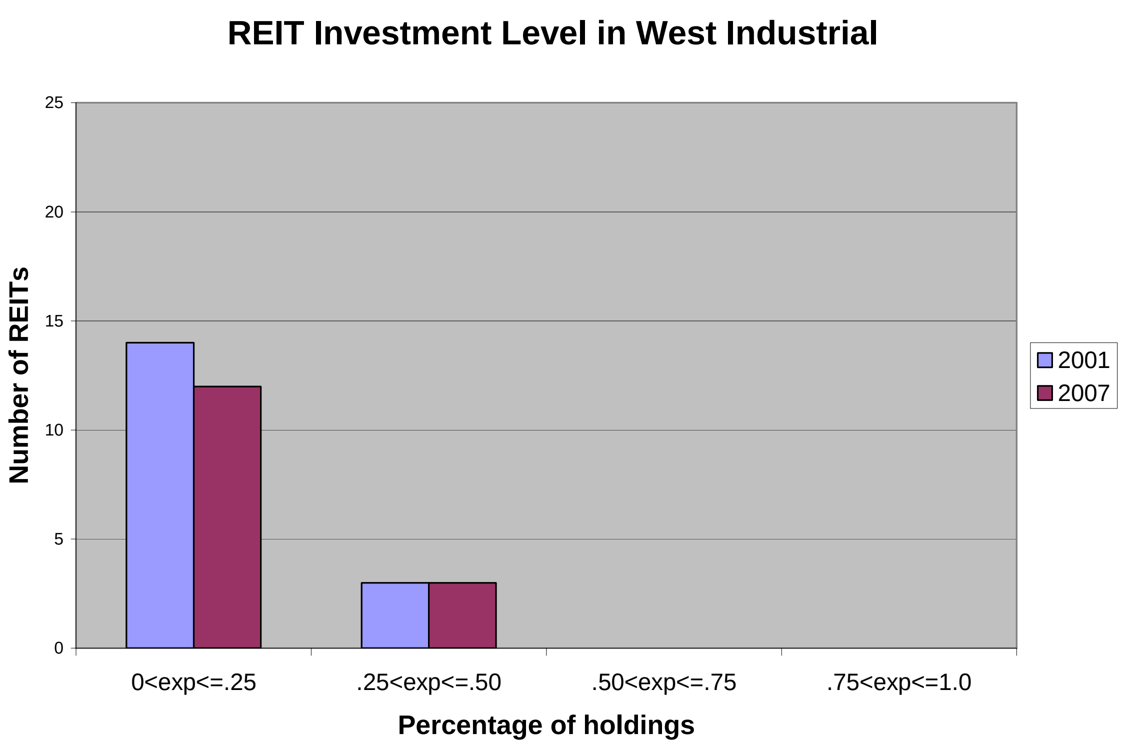

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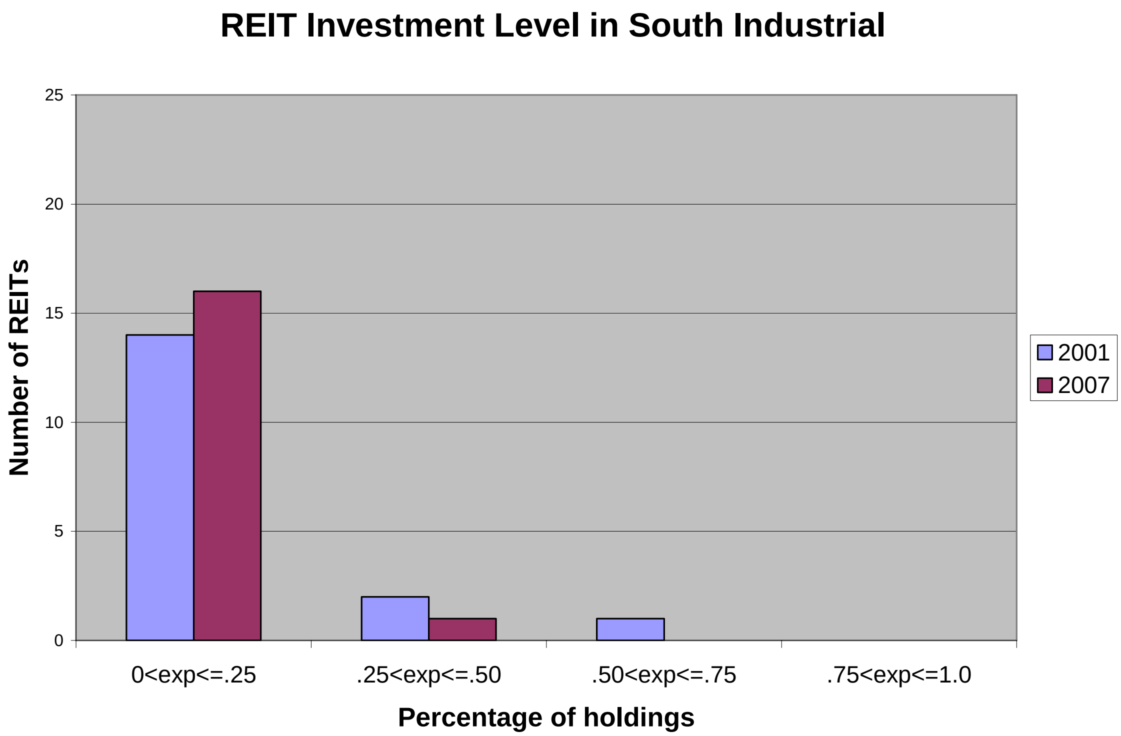

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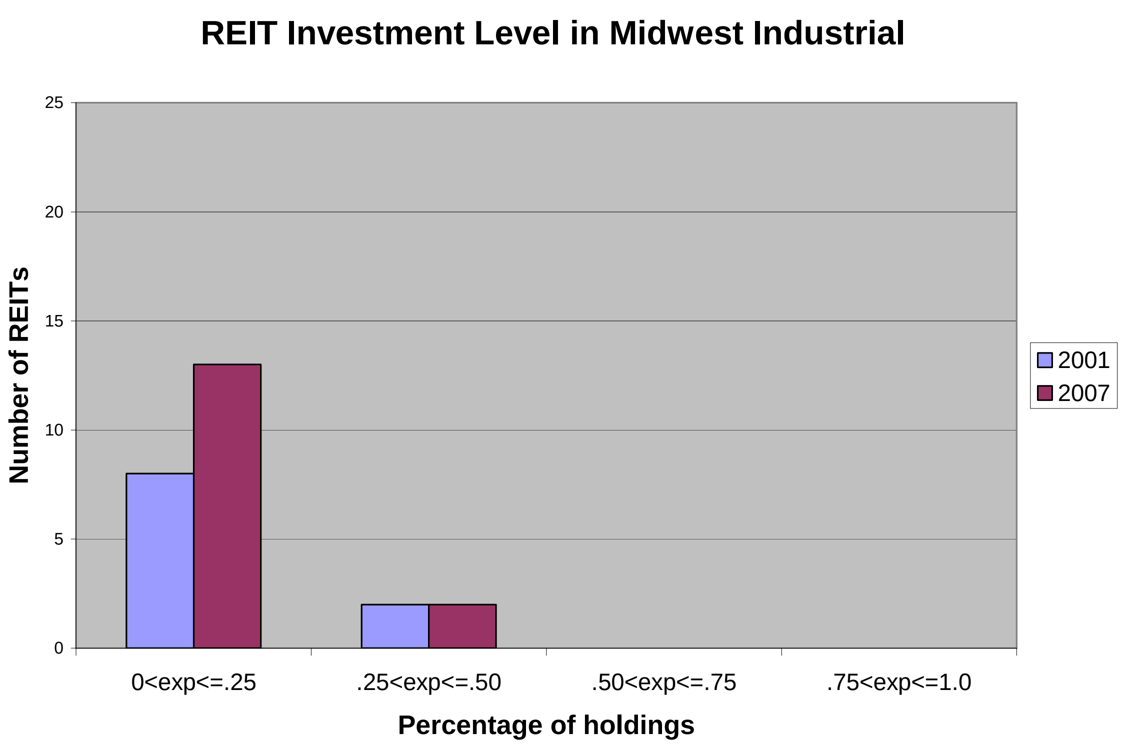

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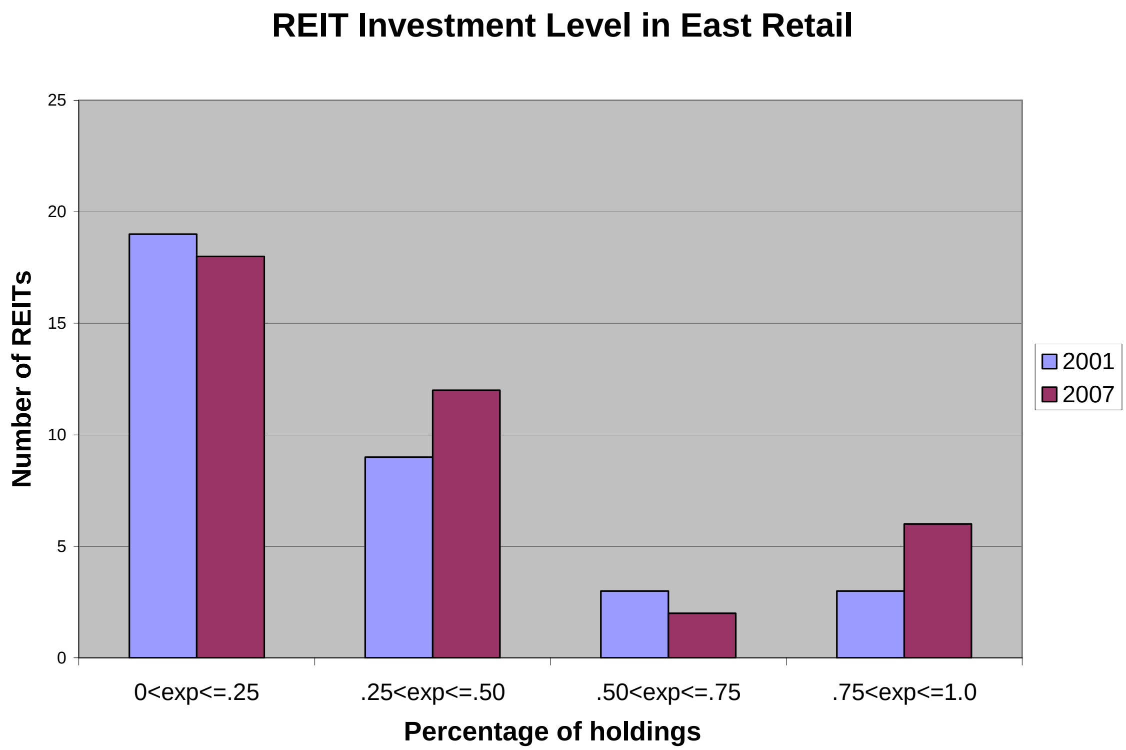

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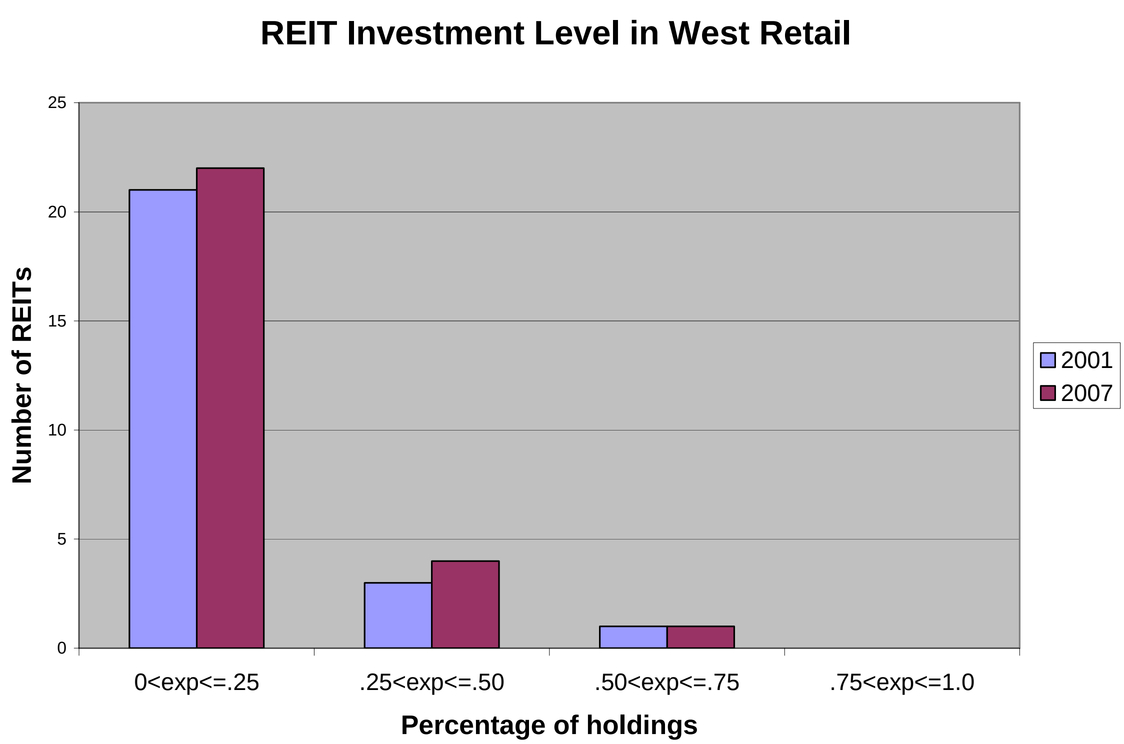

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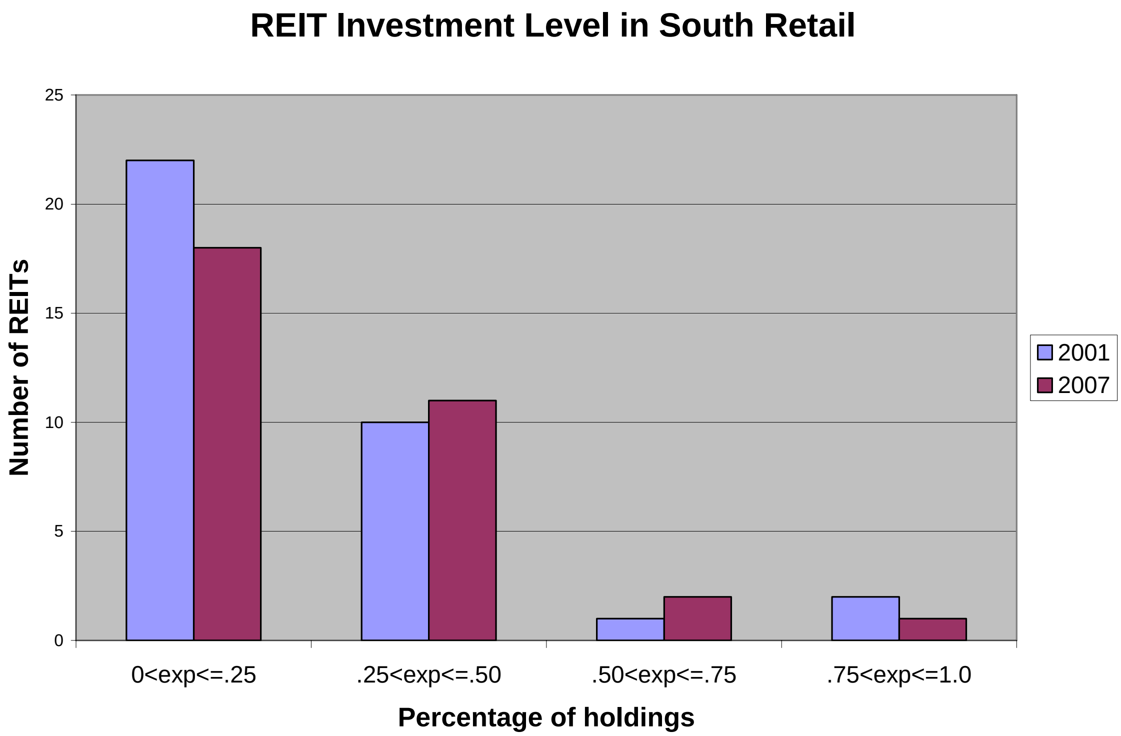

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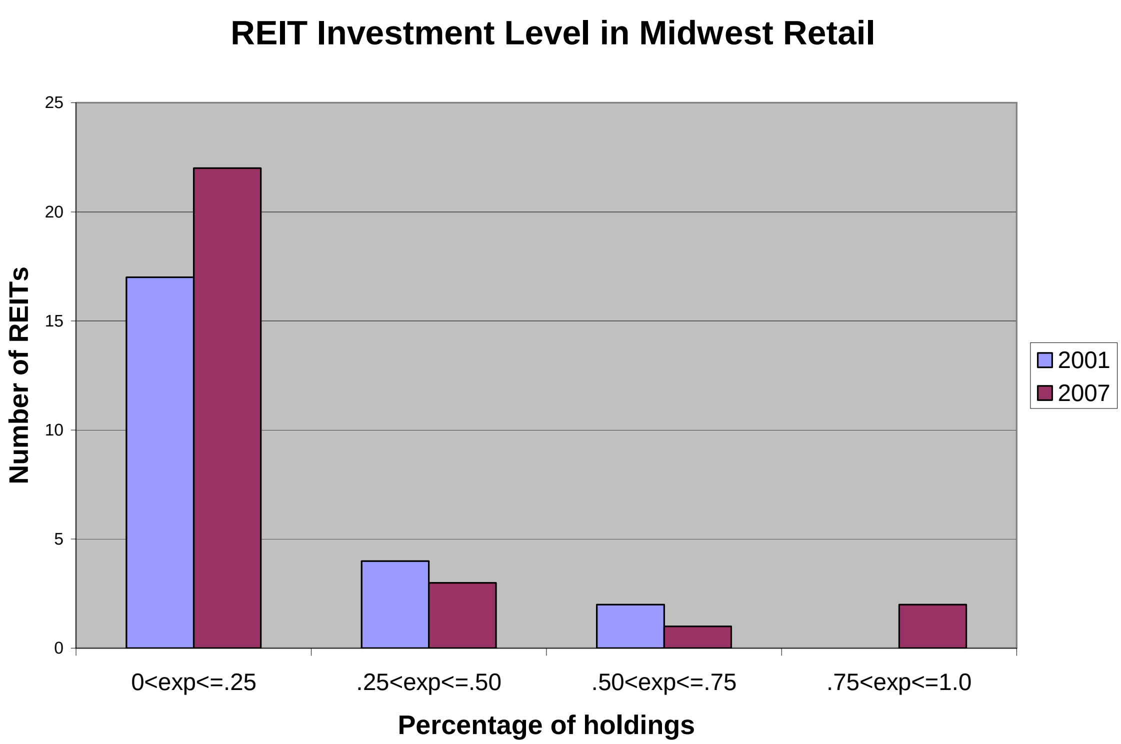

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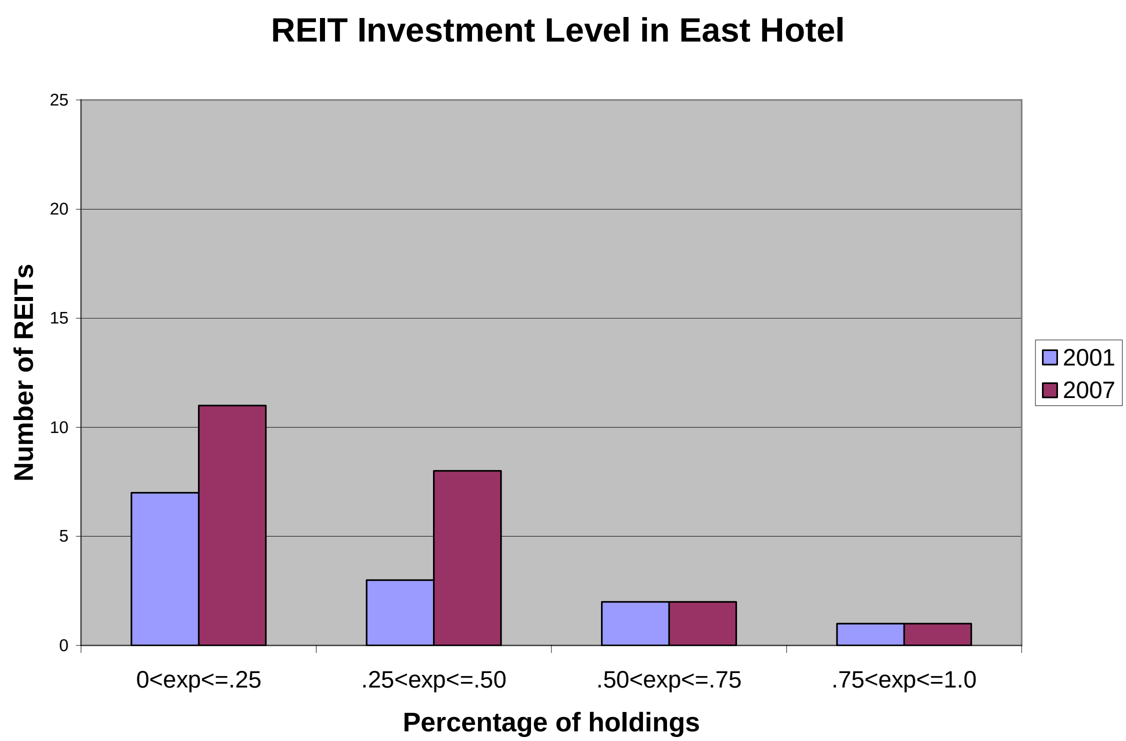

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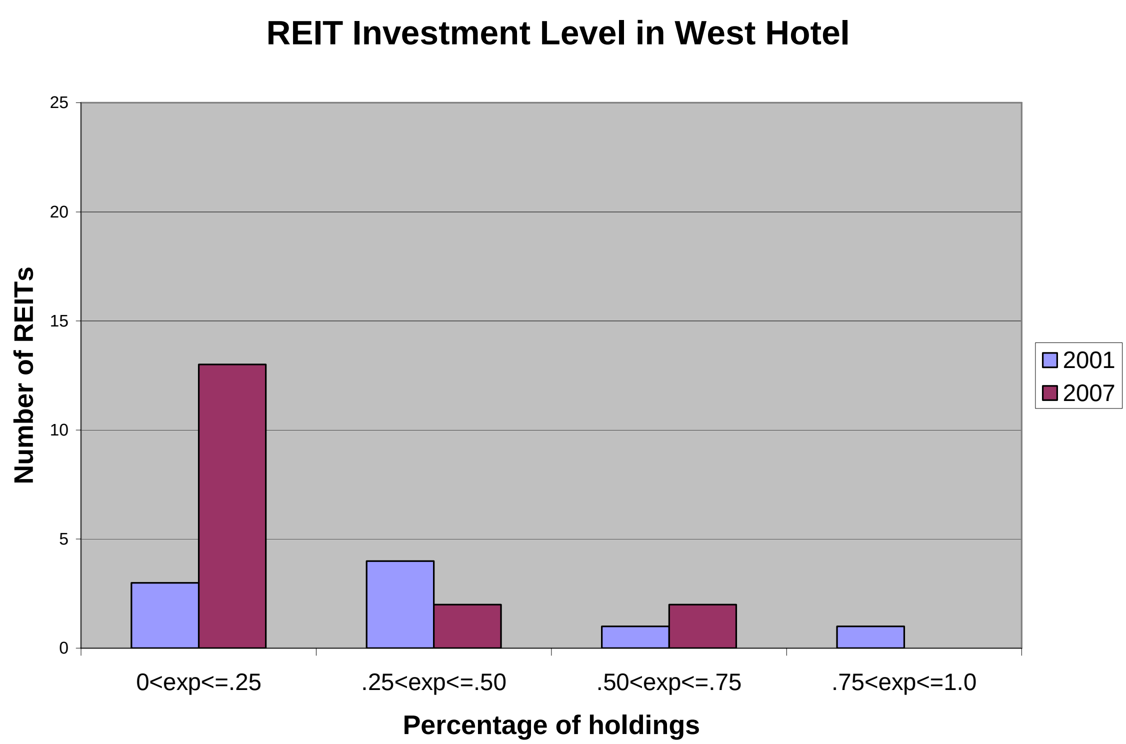

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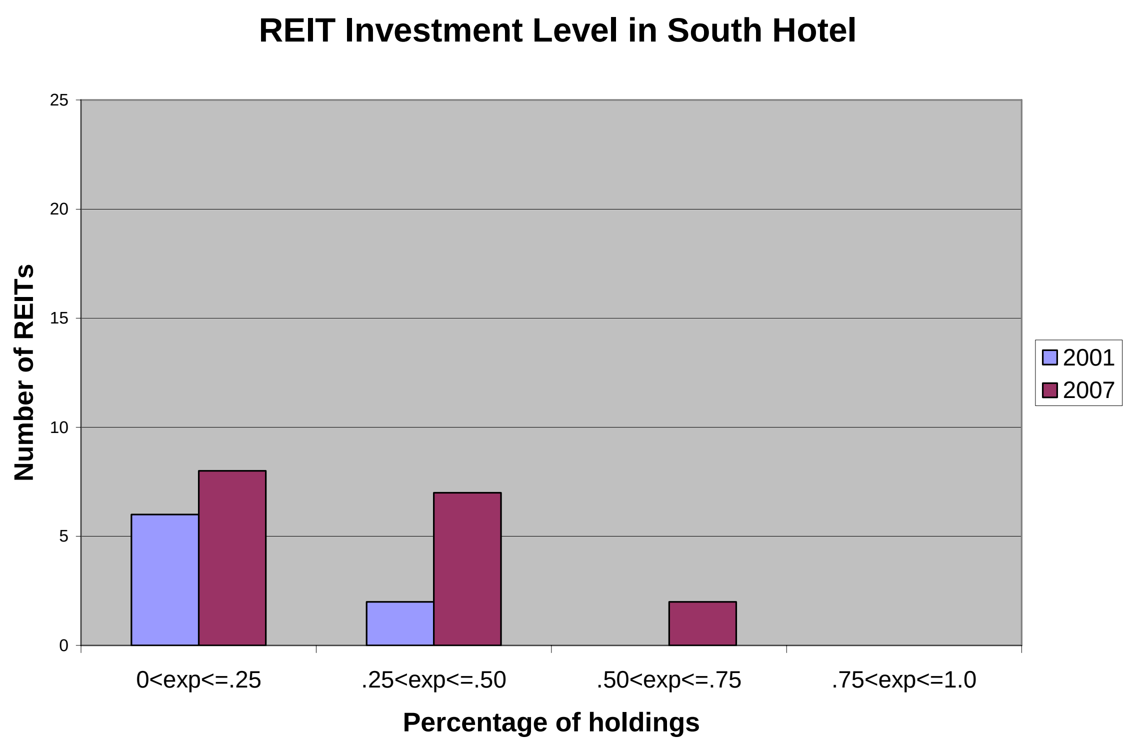

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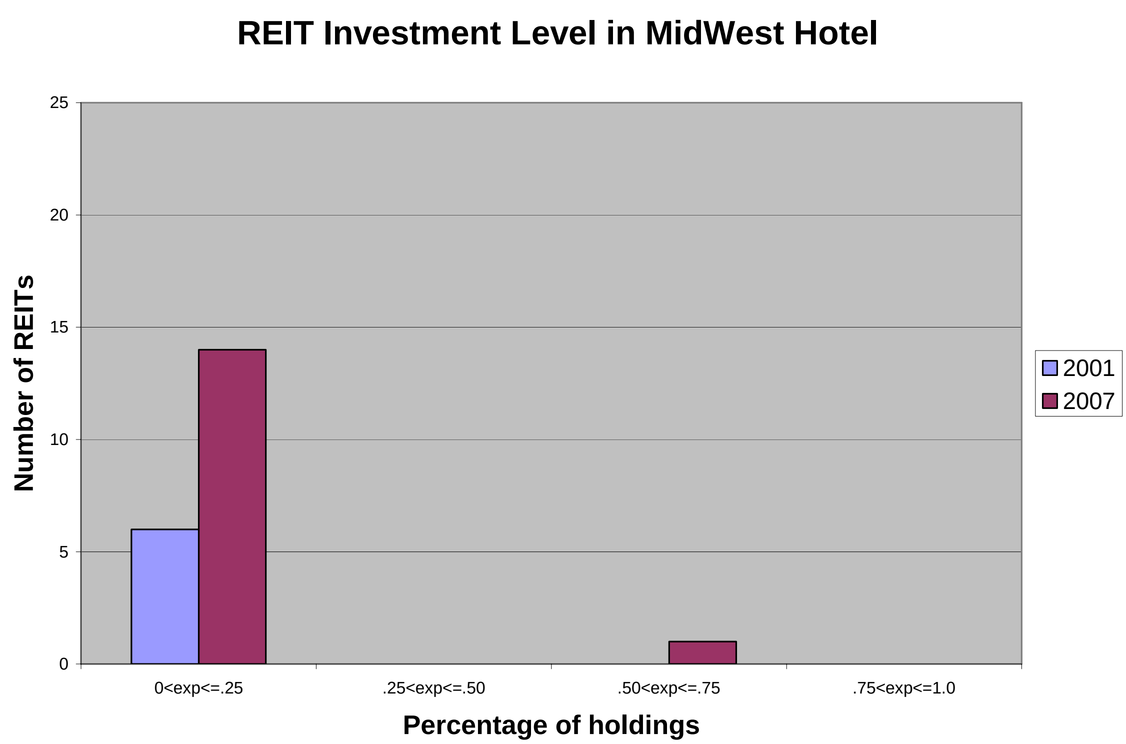

Table (A1) Sample Portfolio Segment Weights: Office Segment 2006

Ticker	REIT Name	Weight	Ticker	REIT Name	Weight
ADC	AGREE REALTY CORP	-0.0669%	EOP	EQUITY OFFICE PROPERTIES TRUST	**11.2565%**
AEC	ASSOCIATED ESTATES REALTY CORP	-0.0578%	EQR	EQUITY RESIDENTIAL	-0.2195%
AFR	AMERICAN FINANCIAL RLTY TRUST	**6.5482%**	EQY	EQUITY ONE INC	-0.1715%
AHT	ASHFORD HOSPITALITY TRUST INC	-0.0663%	ESS	ESSEX PROPERTY TRUST INC	-0.0730%
AIV	APARTMENT INVESTMENT & MGMT CO	-0.1910%	FCH	FELCOR LODGING TRUST INC	-0.0854%
AKR	ACADIA REALTY TRUST	0.0129%	FMP	FELDMAN MALL PROPERTIES INC	-0.0919%
ALX	ALEXANDERS INC	-0.0571%	FPO	FIRST POTOMAC REALTY TRUST	0.2325%
AMB	A M B PROPERTY CORP	-2.2045%	FR	FIRST INDUSTRIAL REALTY TR INC	-1.8430%
ANL	AMERICAN LAND LEASE INC	-0.0434%	FRT	FEDERAL REALTY INVESTMENT TRUST	-0.1594%
APRO	AMERICA FIRST APT INV INC	-0.0042%	FSP	FRANKLIN STREET PROPERTIES CORP	1.8732%
ARC	AFFORDABLE RESIDENTIAL CMNTYS IN	-0.1389%	FUR	WINTHROP REALTY TRUST	1.4293%
ARE	ALEXANDRIA REAL EST EQUITIES INC	**3.2913%**	GGP	GENERAL GROWTH PROPERTIES INC	0.1925%
ASN	ARCHSTONE SMITH TRUST	-0.1421%	GOOD	GLADSTONE COMMERCIAL CORP	0.8687%
AVB	AVALONBAY COMMUNITIES INC	-0.1210%	GPT	GOVERNMENT PROPERTIES TRUST INC	1.3452%
BDN	BRANDYWINE REALTY TRUST	**6.3291%**	GRT	GLIMCHER REALTY TRUST	-0.1869%
BFS	SAUL CENTERS INC	0.3673%	GTY	GETTY REALTY CORP NEW	-0.4120%
BMR	BIOMED REALTY TRUST INC	**2.4223%**	HIH	HIGHLAND HOSPITALITY CORP	-0.0357%
BRE	B R E PROPERTIES INC	-0.0491%	HIW	HIGHWOODS PROPERTIES INC	**5.4487%**
BXP	BOSTON PROPERTIES INC	**6.1842%**	HME	HOME PROPERTIES INC	-0.1070%
CBL	C B L & ASSOCIATES PPTYS INC	-0.2841%	HPT	HOSPITALITY PROPERTIES TRUST	-0.1277%
CDR	CEDAR SHOPPING CENTERS INC	-0.1240%	HRP	H R P T PROPERTIES TRUST	**6.0918%**
CEI	CRESCENT REAL ESTATE EQUITIES CO	**4.1020%**	HT	HERSHA HOSPITALITY TRUST	-0.0528%
CLI	MACK CALI REALTY CORP	**6.2710%**	IRC	INLAND REAL ESTATE CORP	-0.1301%
CLP	COLONIAL PROPERTIES TRUST	**2.0252%**	KIM	KIMCO REALTY CORP	-0.3033%
COE	COLUMBIA EQUITY TRUST INC	1.8615%	KPA	INNKEEPERS U S A TRUST	-0.0606%
CPT	CAMDEN PROPERTY TRUST	-0.1219%	KRC	KILROY REALTY CORP	**2.5052%**
CUZ	COUSINS PROPERTIES INC	**2.3542%**	KRG	KITE REALTY GROUP TRUST	0.0080%
DDR	DEVELOPERS DIVERSIFIED RLTY CORP	-0.3035%	LHO	LASALLE HOTEL PROPERTIES	-0.0367%
DLR	DIGITAL REALTY TRUST INC	**2.9134%**	LRY	LIBERTY PROPERTY TRUST	**2.9066%**
DRE	DUKE REALTY CORP	**2.7320%**	LXP	LEXINGTON CORPORATE PPTYS TRUST	**2.9881%**
DRH	DIAMONDROCK HOSPITALITY CO	-0.0272%	MAA	MID AMERICA APT COMMUNITIES INC	-0.0887%
EGP	EASTGROUP PROPERTIES INC	-0.3451%	MAC	MACERICH CO	-0.2897%
EHP	EAGLE HOSPITALITY PPTYS TR INC	-0.0232%	MDH	M H I HOSPITALITY CORP	-0.0203%
ELS	EQUITY LIFESTYLE PROPERTIES INC	-0.1403%	MLS	MILLS CORP	-0.2601%
ENN	EQUITY INNS INC	-0.0845%	MPG	MAGUIRE PROPERTIES INC	**4.2525%**

Ticker	REIT Name	Weight
MRTI	MAXUS REALTY TRUST INC	-0.0167%
MSW	MISSION WEST PPTYS INC MD	**3.1633%**
NXL	NEW PLAN EXCEL REALTY TRUST INC	-0.3091%
OFC	CORPORATE OFFICE PROPERTIES TR	**4.5739%**
PEI	PENNSYLVANIA REAL ESTATE INVT TR	-0.2277%
PKY	PARKWAY PROPERTIES INC	**3.4696%**
PLD	PROLOGIS	-3.3734%
PPS	POST PROPERTIES INC	-0.0712%
PSB	P S BUSINESS PARKS INC CA	**3.2476%**
REG	REGENCY CENTERS CORP	-0.2493%
RPB	REPUBLIC PROPERTY TRUST	1.5444%
RPI	ROBERTS REALTY INVESTORS INC	0.0320%
RPT	RAMCO GERSHENSON PROPERTIES TR	-0.1594%
SHO	SUNSTONE HOTEL INVESTORS INC NEW	-0.0561%
SKT	TANGER FACTORY OUTLET CENTERS IN	-0.1142%
SLG	S L GREEN REALTY CORP	**4.8072%**
SPG	SIMON PROPERTY GROUP INC NEW	-0.5232%
SPPR	SUPERTEL HOSPITALITY INC	-0.0264%
SUI	SUN COMMUNITIES INC	-0.0897%
TCO	TAUBMAN CENTERS INC	-0.1514%
UBA	URSTADT BIDDLE PROPERTIES INC	-0.0382%
UDR	UNITED DOMINION REALTY TR INC	-0.1360%
UMH	UNITED MOBILE HOMES INC	-0.0483%
VNO	VORNADO REALTY TRUST	**4.6570%**
WRE	WASHINGTON REAL ESTATE INVS TR	1.0995%
WRI	WEINGARTEN REALTY INVESTORS	-0.4078%
WXH	WINSTON HOTELS INC	-0.0586%
		100.0000%