CAIA Member Contribution

Measuring Systematic Biases in Real Estate Returns

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Real Estate is generally considered one of the least liquid asset classes. The are several reasons for the lack of liquidity: the unique nature of each property, the lack of a publicly traded market, the appraisal nature of valuing assets, and the large "chunky" size of each asset. The lack of liquidity has several implications for measuring the risk and performance of real estate.

Publicly traded financial markets are often assumed to be efficient in the sense that there are no asymmetries of information among the market participants. However, this assumption does not apply to the real estate markets where information is costly to acquire and a competitive edge can be gained through in-depth research.

This problem becomes particularly acute with respect to performance measurement. The benchmark chosen to measure the performance of a real estate manager is an important consideration in the assessment of that manager as well as the allocation of capital to that manager. Performance assessment is also important for determining whether a real estate manager can produce alpha or excess returns, and this feeds into the calculation of incentive fees.

More broadly, determining the amount of systematic market risk embedded in real estate portfolios is a key factor in the asset allocation decision for institutional investors. In the risk budgeting process, it is important to have as accurate a measure as possible of the systematic market (or beta) risk associated with every asset class in order to obtain the best diversified portfolio. However, with illiquid asset classes such as real estate, obtaining an accurate measure of the embedded market risk can be difficult.

In this paper, we present a method for measuring the amount of systematic risk in real estate portfolios relative to well recognized market indices. We begin by describing the problem associated with measuring real estate performance. We then measure the sensitivity of the returns to real estate compared to public market indices using an extended market model. We also examine a behavioral element associated with real estate portfolios to determine if there is a systematic bias in the way that real estate managers mark their portfolio holdings. Last, we examine real estate returns to see if there is any seasonal bias in determining valuations.

2. The Problem

The problem with real estate is that there is no "semi-strong" notion of market efficiency where the price of an underlying property reflects all publicly available information. Real estate trades in private transactions. This is in contrast to efficient capital markets which require a liquid trading facility—a stock exchange, an ECN, or some other electronic platform—to allow for transactions to occur that will incorporate the available market information.

Without publicly traded asset prices, real estate managers and investors have to rely on other methods to determine fair value. The most common method to determine fair value is the appraisal approach that relies on prior sales of comparable properties. Using data points obtained from prior sales of similar real estate properties is a standard method to establish the fair value of a real estate property.

However, appraisals tend to lag the current market because they are based on asset sales that occurred in the past, not the present. This lagging can lead to non-synchronous price changes given the movement of the overall financial markets. This is sometimes referred to as stale pricing—that is, the value of a real estate asset may not be "fresh" in the sense that the marked price of the asset may not reflect its current value. Stale pricing can result in underestimating the measure of systematic/market/beta risk associated with real estate assets.

Alternatively, real estate values may be established based on a cash flow analysis using the existing rents contained in the current lease agreements for the property. However, this method also has its "stale effect" because the leases associated with a property may have been negotiated several years in arrears and do not reflect the current state of the rental market.

Last, we need to consider a behavioral element that might be embedded in real estate valuations. Appraisal data is subject to a significant level of estimation and judgment on behalf of the appraiser. As a result it is possible that behavioral biases might creep into the pricing of real estate portfolios. We explore this element in this paper. We, also examine whether there is a seasonal effect in the pricing of real estate portfolios. It is possible that real estate values are subject to an annual rather than behavioral bias.

3. Adjusting Real Estate Returns for Market Exposure

3.1. Contemporaneous Regression Analysis

Real Estate is considered a diversifying asset class from stocks and bonds, but it is not immune from the systematic movements of the broad financial markets. While real estate does not derive all of its return from the up and down movement of the public financial markets, measuring the systematic risk embedded within real estate returns is important for two reasons. First, knowledge of the amount of beta embedded within real estate returns can help separate the return due to market exposure from that earned through the real estate manager's skill. Second, accurate measurement of the amount of beta risk embedded within real estate returns is useful for risk budgeting and asset allocation across an investor's total portfolio.

To separate out the systematic movements of the financial markets, the solution most often pursued is to regress the historical returns from real estate investments on the concurrent returns of a broad-based market index such as the MSCI All Country World Index (ACWI) or the Russell 1000. This gives a measure of the beta or sensitivity of real estate returns to the stock and bond markets.

The regression equation typically takes the form of:

$$R_{i,t}(RE) = \alpha + \beta R_{m,t} + \varepsilon_{i,t} \qquad (1)$$

Where:

$R_{i,t}(RE)$ is the return to real estate at time t

$R_{m,t}$ is the return on a broad-based market index at time t

β is a measure of the systematic exposure of real estate returns to the broad-based market index

$\varepsilon_{i,t}$ is a residual term which measures the variation of real estate returns that are not explained by movements in the broad-based market index or the real estate manager's skill

a is the return due to the real estate manager's skill

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This is a simple one-factor regression model. Equation 1 can be turned around to produce:

$$R_{i,t}(RE) - \beta R_{m,t} = \alpha + \varepsilon_{i,t} \qquad (2)$$

Equation 2 is the risk-adjusted formula for real estate returns. It separates the returns from real estate into two components: market (beta) returns and excess returns which can be a measure of manager skill. Equation 2 can be further refined by subtracting the return earned from investing in U.S. Treasury bills from the left hand side of the equation. Real estate returns should at least be able to outperform a cash rate of return—if not then there would be no demand to invest capital in this risky asset class.
Equation 2 can be expressed as:

$$\left[R_{i,t}(RE) - Tbill\right] - \beta\left[R_{m,t} - Tbill\right] = \alpha + \varepsilon_{i,t} \qquad (3)$$

where

$\left[R_{i,t}(RE) - Tbill\right]$ represents the net of fees return earned by real estate in excess of a cash rate of return;
$\left[R_{m,t} - Tbill\right]$ represents the return on the market index in excess of the cash rate of return;
a is the risk-adjusted excess return earned by the real estate manager; and
$\varepsilon_{i,t}$ is an indication of residual effects that are not explained by the data; it indicates random noise in the data.

Equation 3 can be used as a performance measure for real estate. First, the term β (beta) is a measure of the systematic risk of the real estate portfolio in relation to the market index. A value of beta greater than one indicates a real estate portfolio that has greater sensitivity to the movements of the overall stock market than a diversified basket of stocks. Conversely, a beta value less than one indicates a portfolio that has less sensitivity to the movements of the overall stock market.

The term a (alpha) is the intercept of the equation and it measures the return earned by the real estate portfolio after taking into account the effects of the broad stock or bond market and the current cash rate of return. The intercept represents the excess risk-adjusted return earned by the real estate manager over and above that for the market return and a cash return. This term represents the skill of the real estate manager.[i]

Notice that Equation 3 contains two residual terms, alpha and epsilon (ε). Epsilon represents random noise in the data: in other words it is not attributed to manager skill. So how do we know whether the residual term is alpha or epsilon? This is where statistics come into play. If the residual term is statistically significant from zero, then this is a demonstration of a consistent economic effect, i.e., alpha or manager skill. However, if the residual term is not statistically significant, then this is an indication of only random noise—ε—and not manager skill.

Another problem is that the returns from the NCREIF Property Index (NPI) obscure the actual or "true" real estate return. To extract the true returns, an unsmoothing procedure must be used. The simplest is a first-order autoregressive reverse filter. Equation 4 provides the unsmoothed capital growth rates for direct real estate investment. This method looks at the NPI return as a combination of the current true real estate return and a lagged component for the prior index value:

$$NPI_T = (1-a) \times (\text{True RE Returns}) + a \times NPI_{T-1} \qquad (4)$$

The above equation says that the current NPI index return is equal to a component of the true underlying real estate return plus a component from the NPI return of the prior period. An autoregressive process with more than one lag provides a more generalized model. This allows for a more extensive lagging effect typically associated with illiquid asset classes.

$$NPI_T = (1-a-b)\times(\text{True RE Returns}) + a\times NPI_{T-1} + b\times NPI_{T-2} \quad (5)$$

We can re-arrange Equation 5 to get an estimate of the True RE return:[ii]

$$\text{True Return} = \left(NPI_T - a\times NPI_{T-1} - b\times NPI_{T-2}\right)/(1-a-b) \quad (6)$$

3.2. Multi-Period Regression Analysis

We discussed above that the returns to real estate investing may lag that of the public securities markets. This means that examining real estate returns based on contemporaneous market returns may not fully reveal the extent to which real estate returns depend upon the returns to the broad stock or bond market. Therefore, the simple one period regression models we performed above may not provide accurate estimates of the systematic risk of real estate returns as measured by β or the risk-adjusted excess return as measured by a, the regression intercept.

In fact, the estimates of beta may be biased downwards while the estimates of alpha may be biased upwards because real estate pricing may not occur contemporaneously with changes in the public securities markets. This lack of non-synchronous pricing might then be embedded in the alpha intercept. This would inflate the alpha coefficient to a greater extent that we might observe if we could capture these lagged pricing effects. In other words, what we label skill by the real estate manager as measured by the alpha intercept in the single period regressions might, in fact, reflect the delayed impact of systematic market risk instead of manager skill. To solve the problem of stale pricing, Equation 1 can be expanded to include multi-period pricing effects:[iii]

$$R_{i,t}(RE) = \alpha + \beta_0 R_{m,t} + \beta_1 R_{m,t-1} + \beta_2 R_{m,t-2} + \beta_3 R_{m,t-3} + \ldots + \varepsilon_{i,t} \quad (7)$$

Equation 7 represents a model where the returns to real estate in period t are regressed against the contemporaneous returns to the market as well as the lagged returns to the market from prior periods t − 1, t − 2, t − 3, and so forth. Equation 7 is a "multi-period" extension of regression Equation 1. In Equation 7, we use the real returns unsmoothed from the NPI as described in Equation 6.

If the returns to real estate are due to stale valuation methods, we should see a significant influence from prior market returns. That is, stale or managed pricing may result in a delay between the time that changes in the value of the broad securities market are observed and the time when these changes in value are reflected in the returns to real estate portfolios. By including prior market returns in our regression equation, we can observe the non-synchronous or delayed market effects on real estate returns.

In Equation 7, the summed beta of β0 + β1 + β2 + β3 + …, provides a more accurate measure of how the returns to real estate co-vary with the public securities market. The reason we can do this is that beta coefficients are linearly additive. In other words, by summing the regression coefficients for both contemporaneous and lagged market effects we can obtain a better measure of the systematic risk associated with real estate. In addition, by taking into account both contemporaneous and lagged stock/bond market effects, we should also obtain a better estimate of alpha, the measure of excess returns associated with the real estate market.

With respect to Equation 7, we can perform the same transformations to achieve the same risk-adjusted return (in excess of a cash rate) demonstrated in Equation 3. Equation 8 presents this transformation.

$$\begin{aligned}\alpha + \varepsilon_{i,t} = &\left[R_{i,t}(RE) - Tbill\right] - \beta_0\left[R_{m,t} - Tbill\right] - \beta_1\left[R_{m,t-1} - Tbill\right] \\ &- \beta_2\left[R_{m,t-2} - Tbill\right] - \beta_3\left[R_{m,t-3} - Tbill\right]\end{aligned} \quad (8)$$

We regress the returns to real estate on the contemporaneous market return as well as the market return for the several prior quarters. We include as many beta coefficients as are statistically significant. In this way, we can observe the full impact of the public securities markets on the returns to real estate.[iv]

3.3. Prior Research

The idea of measuring the systematic risk of illiquid asset classes with lagged market returns is not new. Anson (2002, 2007) demonstrates a significant lagged beta effect associated with private equity portfolios. He finds up to four quarters of market returns are significant in measuring the amount of systematic risk embedded in private equity portfolios. When summing across lagged betas, Anson finds that the systematic risk component of leveraged buyouts, venture capital, and mezzanine finance is approximately double the estimate of market exposure using a one-period model. At the same time, the size of alpha—the measure of private equity manager skill—decreases significantly when lagged betas are included.

Anson also finds a significant and consistent behavioral element in the pricing of private equity portfolios. He splits the data into two binary sets—positive financial markets and negative financial markets. He finds that private equity managers are quick to mark down the value of their private investments during negative financial markets, but slow to mark up the value of their private investments in positive markets—demonstrating a rule of conservatism in their portfolio valuations.

Woodward (2010) finds similar results to Anson (2002, 2007); that the measure of market risk embedded in private equity portfolios is greater when including lagged betas. However, using a different database, Woodward finds significant lagged betas for private equity that extend out for six quarters.[v] She also includes a correction for autocorrelation of the residuals to ensure that her beta estimates are minimum variance and unbiased.

The lagged beta effect has also been observed in hedge fund returns. Asness, Krail and Liew (2001) find that many hedge fund strategies have lagged market exposure that extends up to four months of market returns. Marcato and Key use different unsmoothing models to reveal the true real estate return. They find that different autoregressive unsmoothing techniques lead to different asset allocation results for real estate in a diversified portfolio.

Last, Stefek and Suryanarayanan (2012) examine the link between public market real estate returns and private market real estate. They focus on the UK real estate market and use the performance of Real Estate Investment Trusts (REITs) as a public measure of real estate returns and the IPD UK All Property Index for private market returns. They use a lagging model and find that private real estate returns are more strongly related to lagged public REIT returns than current REIT returns.

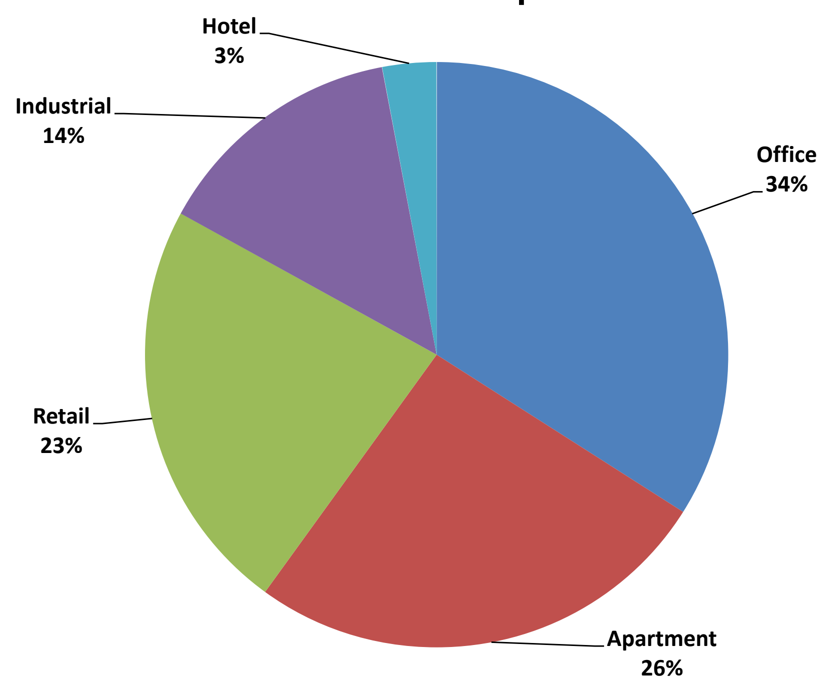
4. Empirical Results

4.1. Contemporaneous Beta Models

We first use a single-period model to measure the systematic market risk embedded in Real Estate Returns. As the dependent variable we use the NCREIF (National Council of Real Estate Investment Fiduciaries) Property Index (NPI). One requirement for NCREIF membership is that its members share their information on their real estate portfolios. Every quarter, members of NCREIF submit their data about their real estate properties that they own to support the NPI. NCREIF aggregates this information from its members on an extremely confidential basis and builds indices based on the member data. It then publishes these indices for use by its members and the real estate industry.

The NPI is a proxy for the performance of direct investments in real property. Specifically, the NPI provides the total return for an institutional grade real estate portfolio held by large US investors. Real estate properties are typically managed by investment fiduciaries on behalf of large institutional investors in the US such as endowments, foundations, pension funds, and high-net-worth investors. As of 2011, the NPI had almost 6,500 properties and the index was worth more than $272 billion. Exhibit 1 shows the composition of the NPI.

Exhibit 1: NPI Composition



Because the turnover of real estate properties is infrequent, the NPI is based on appraised values, rather than market transactions. Appraised values can be based on comparable sales of similar properties, or on a discounted cash flow method. Both of these methods have lagging problems. First, comparable sales are market transactions that occurred in the past and their values are used to appraise real estate in the present. Second, the cash flow analysis is based on leases signed in the past and will not reflect the current rental market. As a result, both appraisal methods are flawed in that they are potentially tied to past market information instead of current data. This is the very root of the problem we attempt to examine—that real estate values lagged the broader financial markets in their valuations and this lagged effect leads to underestimation of their true market or beta exposure as well as an overestimation of their diversification potential.

For the independent variable, we use three broad financial market indexes: MSCI ACWI for international stock market risk, the Russell 1000 for US financial market risk, and the Blackrock Aggregate Bond index.

Exhibit 2: Single Period Models

Single Period Models	Value	T Stat	P Value	R-Square	Correlaton
NPI vs. MSCI ACWI					
Intercept	1.68%	6.056	0.00%	2.51%	0.158
Beta	0.043	1.36	17.70%		
NPI vs. Russell 1000					
Intercept	1.69%	6.09	0.00%	1.54%	0.124
Beta	0.037	1.15	25.00%		
NPI vs. Blackrock Agg.					
Intercept	2.40%	4.089	0.02%	1.51%	-0.123
Beta	-0.200	-0.83	41.00%		

Exhibit 2 presents the results for our single period market model. The single period betas for MSCI ACWI, Russell 1000, and the bond index are, respectively, 0.043, 0.037, and -0.200. These beta measures are weakly significant at the 18% to 41% level—certainly not strong economic statistics. In addition, the R-Square measures for each of these beta equations are low—in the range of 1.5% to 2.5%. Last, each of the alpha intercept terms is large and range from 1.68% to 2.40% and each is statistically significant at the 0.02% level.

These results indicate that there is a limited exposure to the public security markets embedded in real estate returns. When we translate the R-Square measures into correlation coefficients (MSCI ACWI: 15.8%; Russell 1000: 12.4%; Barclays Aggregate: -12.3%) we could conclude that real estate is an effective diversification tool in the asset allocation/portfolio construction process. Last, the positive and statistically significant intercept terms indicates that there is considerable excess return associated with real estate that is not accounted for by the systematic movement of the broad financial markets.

However, we remind ourselves that real estate returns are subject to delayed or lagged pricing through the appraisal process. Therefore, the contemporaneous regression of real estate returns on public market returns may not capture the full amount of systematic risk embedded in real estate returns.

4.2. Lagged Beta Models

Consequently, we turn to our multi-period regression analysis to measure the full amount of systematic risk embedded in real estate returns. Starting with MSCI ACWI, we find that there is statistically significant market risk embedded in real estate returns for six periods of data. Even Beta(-5) is significant at the 8% level (see Exhibit 3a). This indicates that real estate returns have embedded systematic market risk up to five prior quarters. When we sum the lagged betas associated with global stocks, we find that the beta of real estate is 0.57—much greater than our single period model. In addition, the R-Square of real estate returns with public equity returns is much higher in the multi-period model—37%. Last, the alpha intercept term declines significantly—down to 0.96% per quarter, although it is still statistically significant.

We also examine the last decade splitting the time period into two sub-periods. The first half of the last decade, 2000-2005 was associated with the build-up of the housing and real estate bubble. We would expect to see less correlation and systematic risk from an asset class that is experiencing a valuation bubble. Generally, a "bubble" describes the state of the world where one asset class becomes disconnected with the fundamentals of the underlying economy and from the valuations of other asset classes that remain grounded in economic reality. However, after the housing bubble burst in 2006, we would expect to see the systematic risk of the real estate market to be more transparent as it would reflect the same economic fundamentals that affect the broad financial markets.

Exhibit 3a supports this hypothesis. The total beta for MSCI ACWI during the period 2000-2005 is only 0.23 with an R-Square of 45%. For the period of 2006-2011, the total beta is 0.97 with an R-Square of 90%. It is clear from this analysis that there is a significant systematic market risk embedded in real estate returns, and this lagged effect extends for up to six quarters. When the real estate markets are affected by the common macroeconomic conditions as other asset classes, the lagged systematic risk is considerable.

We find similar results when we use the Russell 1000 as our proxy for market returns (see Exhibit 3b). Once again, the lagging effect extends out to five quarters of market returns. There is a significant lagged beta effect for the full time period. Similar to the MSCW ACWI the lagged market risk effect is greatest after the real estate bubble. Over this time period, the lagged betas sum up to 0.84 and achieve an R-Square of 92%. However, the alpha

Exhibit 3a: Multi Period Analysis NPI vs. Lagged MSCI ACWI

NPI vs. Lagged MSCI ACWI	1990-2011			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.0096	0.0033	2.9423	0.42%
ACWI(0)	0.1012	0.0343	2.9462	0.42%
ACWI(-1)	0.1140	0.0344	3.3126	0.14%
ACWI(-2)	0.0937	0.0349	2.6828	0.88%
ACWI(-3)	0.1107	0.0349	3.1680	0.22%
ACWI(-4)	0.0912	0.0351	2.5993	1.11%
ACWI(-5)	0.0620	0.0350	1.7727	8.00%
Total Beta	0.573			
R-Square	37%			
Correlation Coefficient	61%			

NPI vs. Lagged MSCI ACWI	2000-2005			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.0281	0.0030	9.4514	0.00%
ACWI(0)	0.0302	0.0368	0.8227	42.21%
ACWI(-1)	0.0225	0.0339	0.6633	51.60%
ACWI(-2)	0.0428	0.0345	1.2410	23.15%
ACWI(-3)	0.0465	0.0344	1.3516	19.42%
ACWI(-4)	0.0769	0.0336	2.2902	3.51%
ACWI(-5)	0.0109	0.0335	0.3269	74.78%
Total Beta	0.230			
R-Square	45%			
Correlation Coefficient	67%			

NPI vs. Lagged MSCI ACWI	2006-2011			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.0040	0.0040	0.9878	33.71%
ACWI(0)	0.2392	0.0413	5.7943	0.00%
ACWI(-1)	0.2311	0.0440	5.2475	0.01%
ACWI(-2)	0.0414	0.0475	0.8723	39.52%
ACWI(-3)	0.2553	0.0484	5.2771	0.01%
ACWI(-4)	0.1983	0.0481	4.1229	0.07%
ACWI(-5)	0.0080	0.0442	0.1821	85.77%
Total Beta	0.973			
R-Square	90%			
Correlation Coefficient	95%			

Exhibit 3b: Multi Period Analysis NPI vs. Lagged RU10000

NPI vs. Lagged RU1000	1990-2011			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.0107	0.0028	3.7875	0.03%
Russell 1000 (0)	0.0320	0.0303	1.0536	29.55%
Russell 1000 (-1)	0.0613	0.0310	1.9755	5.20%
Russell 1000 (-2)	0.0690	0.0304	2.2661	2.64%
Russell 1000 (-3)	0.0682	0.0304	2.2450	2.78%
Russell 1000 (-4)	0.0763	0.0296	2.5747	1.21%
Russell 1000 (-5)	0.0616	0.0298	2.0674	4.22%
Total Beta	0.368			
R-Square	33%			
Correlation Coefficient	57%			

NPI vs. Lagged RU1000	2000-2005			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.0257	0.0020	12.8868	0.00%
Russell 1000 (0)	0.0064	0.0235	0.2731	78.76%
Russell 1000 (-1)	0.0123	0.0211	0.5842	56.56%
Russell 1000 (-2)	0.0260	0.0207	1.2589	22.25%
Russell 1000 (-3)	0.0343	0.0206	1.6606	11.24%
Russell 1000 (-4)	0.0411	0.0200	2.0538	5.33%
Russell 1000 (-5)	0.0208	0.0203	1.0237	31.82%
Total Beta	0.141			
R-Square	41%			
Correlation Coefficient	64%			

NPI vs. Lagged RU1000	2006-2011			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.0077	0.0029	2.6449	1.84%
Russell 1000 (0)	0.1154	0.0356	3.2400	0.55%
Russell 1000 (-1)	0.1515	0.0399	3.7916	0.18%
Russell 1000 (-2)	0.1014	0.0409	2.4764	2.57%
Russell 1000 (-3)	0.2063	0.0405	5.0990	0.01%
Russell 1000 (-4)	0.1624	0.0403	4.0262	0.11%
Russell 1000 (-5)	0.1018	0.0408	2.4926	2.49%
Total Beta	0.839			
R-Square	92%			
Correlaton Coefficient	96%			

Exhibit 3c: Multi Period Analysis NPI vs. Lagged Bonds

NPI vs. Lagged Bonds	1990-2011		
	Coefficients	Standard Error	t Stat
Intercept	0.0271	0.0054	5.0297
BlackRock Aggregate(0)	-0.1995	0.1404	-1.4204
BlackRock Aggregate(-1)	-0.1734	0.1404	-1.2347
BlackRock Aggregate(-2)	-0.1074	0.1396	-0.7694
BlackRock Aggregate(-3)	-0.0571	0.1393	-0.4100
Total Beta	-0.537		
R-Square	4.5%		
Correlation Coefficient	-21%		

NPI vs. Lagged Bonds	2000-2005		
	Coefficients	Standard Error	t Stat
Intercept	0.0278	0.0099	2.8080
BlackRock Aggregate(0)	-0.2332	0.2577	-0.9046
BlackRock Aggregate(-1)	-0.1668	0.2579	-0.6467
BlackRock Aggregate(-2)	-0.0718	0.2592	-0.2769
BlackRock Aggregate(-3)	-0.0012	0.2532	-0.0049
Total Beta	-0.473		
R-Square	1.6%		
Correlation Coefficient	-13%		

NPI vs. Lagged Bonds	2006-2011		
	Coefficients	Standard Error	t Stat
Intercept	0.0211	0.0230	0.9186
BlackRock Aggregate(0)	-0.3908	0.5621	-0.6952
BlackRock Aggregate(-1)	-0.1379	0.5821	-0.2369
BlackRock Aggregate(-2)	-0.0891	0.5728	-0.1555
BlackRock Aggregate(-3)	0.0525	0.5639	0.0932
Total Beta	-0.565		
R-Square	3.2%		
Correlation Coefficient	-18%		

Exhibit 3d: Multi Period Analysis NPI vs. Lagged REIT

NPI vs. Lagged REIT	1990-2011		
	Coefficients	*Standard Error*	*t Stat*
Intercept	0.0057	0.0031	1.8276
Beta(0)	0.0484	0.0239	2.0259
Beta)-1)	0.0408	0.0246	1.6614
Beta(-2)	0.0677	0.0242	2.8000
Beta(-3)	0.0550	0.0242	2.2696
Beta(-4)	0.0815	0.0238	3.4240
Beta(-5)	0.0530	0.0239	2.2202
Beta(-6)	0.0505	0.0235	2.1463
Total Beta	0.397		
R-Square	37%		

NPI vs. Lagged REIT	2000-2005		
	Coefficients	*Standard Error*	*t Stat*
Intercept	0.0163	0.0060	2.7056
Beta(0)	0.0635	0.0428	1.4846
Beta(-1)	0.0404	0.0420	0.9626
Beta(-2)	0.0473	0.0384	1.2298
Beta(-3)	0.0319	0.0397	0.8037
Beta(-4)	0.0507	0.0401	1.2643
Beta(-5)	0.0224	0.0414	0.5419
Beta(-6)	0.0009	0.0380	0.0240
Total Beta	0.257		
R-Square	23%		

NPI vs. Lagged REIT	2006-2011		
	Coefficients	*Standard Error*	*t Stat*
Intercept	-0.0015	0.0045	-0.3317
Beta(0)	0.0754	0.0282	2.6741
Beta(-1)	0.0687	0.0301	2.2795
Beta(-2)	0.0912	0.0312	2.9200
Beta(-3)	0.1083	0.0302	3.5865
Beta(-4)	0.1142	0.0294	3.8816
Beta(-5)	0.0574	0.0284	2.0227
Beta(-6)	0.0725	0.0276	2.6239
Total Beta	0.588		
R-Square	83%		

intercept during this last period of 0.77% remains statistically significant at 2%.

For the bond index, we don't find any of the lagged betas to be significant (at 10%) over any time period. There is no improvement over the single-period model. This is further supported by the fact that there is almost no change in the correlation coefficient between the single-and multi-period model and the R-Square measure is no higher than 4.5% for the full time period. The only odd result is that the alpha intercept declines slightly over the 2006-2011 periods and becomes statistically insignificant. Nonetheless, our conclusion is that there is very little lagged systematic bond (duration) risk embedded in unlevered real estate returns.

4.3. Behavioral Beta Models

Our results indicate that private real estate portfolios reflect changes in the prices of marketable securities over a period of time up to five quaters. In other words, there is non-synchronous (lagged) pricing between private real estate portfolios and public stock market returns. We next examine whether there is a systematic behavioral bias associated with the valuation of private real estate.

The non-contemporaneous impact of market returns on private real estate portfolios could be due to the structure of the real estate market. That is, illiquid properties which are marked by appraisal only when there are observable, but infrequent events such as comparable property sales. Alternatively, the lagged impact of market returns on real estate portfolios could be due to real estate managers who actively manage the pricing of their portfolios. It is possible that property managers mark the value of their portfolios up or down when it is most favorable to do so. This is a behavioral aspect that can arise when there is discretion in the valuation of illiquid portfolios.

One way to detect a behavioral bias is to divide the world up into two mutually exclusive states—Up Markets and Down Markets. We accomplish this division using a dummy variable.

A dummy variable is a way to split the world into two distinct states. In State One, the public securities market performs well (Up Markets). In State Two, the public market performs poorly (Down Markets). Dummy variables are often referred to as binary variables because of the way they divide the world into two separate categories. Dummy variables are often multiplied against the independent variables in the regression equation to capture this binary view of the world. Our new equation looks like this:

$$R_{it}\left(RE\right)-Tbill=\alpha+D\times\sum_{j=0}\beta_j\left\lfloor R_{m,t-j}-Tbill\right\rfloor+\varepsilon_{i,t} \qquad (9)$$

Exhibit 4a: ACWI and Dummy Variables 1990-2011

ACWI Up Markets **1990-2011**
SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.423
R Square	0.179
Adjusted R Square	0.113
Standard Error	0.033
Observations	82.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	6.000	0.018	0.003	2.719	0.019
Residual	75.000	0.082	0.001		
Total	81.000	0.100			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*
Intercept	-0.009	0.008	-1.093	0.278	-0.026
ACWI (0)	0.073	0.070	1.039	0.302	-0.067
ACWI (-1)	0.054	0.070	0.775	0.441	-0.085
ACWI (-2)	0.158	0.070	2.274	0.026	0.020
ACWI (-3)	0.137	0.070	1.967	0.053	-0.002
ACWI (-4)	0.172	0.069	2.485	0.015	0.034
ACWI (-5)	0.099	0.069	1.424	0.159	-0.039
Total Beta	0.693				

ACWI Down Markets **1990-2011**
SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.634
R Square	0.401
Adjusted R Square	0.344
Standard Error	0.021
Observations	81.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	7.000	0.022	0.003	6.991	0.000
Residual	73.000	0.032	0.000		
Total	80.000	0.054			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*
Intercept	0.032	0.003	10.098	0.000	0.026
ACWI (0)	0.092	0.052	1.785	0.078	-0.011
ACWI (-1)	0.134	0.052	2.554	0.013	0.029
ACWI (-2)	0.087	0.052	1.676	0.098	-0.017
ACWI (-3)	0.113	0.052	2.195	0.031	0.010
ACWI (-4)	0.073	0.048	1.509	0.136	-0.023
ACWI (-5)	0.089	0.047	1.881	0.064	-0.005
Total Beta	0.589				

Exhibit 4b: ACWI and Dummy Variables 2004-2011

ACWI UP Markets **2004-2011**
SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.530
R Square	0.281
Adjusted R Square	0.060
Standard Error	0.034
Observations	31.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	7.000	0.011	0.002	1.563	0.196
Residual	24.000	0.028	0.001		
Total	31.000	0.039			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*
Intercept	-0.006	0.014	-0.455	0.653	-0.035
ACWI (0)	-0.010	0.055	-0.182	0.856	-0.120
ACWI (-1)	0.025	0.116	0.212	0.834	-0.215
ACWI (-2)	0.109	0.117	0.935	0.359	-0.132
ACWI (-3)	-0.080	0.119	-0.672	0.508	-0.326
ACWI (-4)	0.204	0.105	1.944	0.064	-0.013
ACWI (-5)	0.178	0.109	1.637	0.115	-0.046
Total Beta	0.426				

ACWI Down Markets **2004-2011**
SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.963
R Square	0.927
Adjusted R Square	0.905
Standard Error	0.011
Observations	31.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	7.000	0.036	0.005	41.745	0.000
Residual	23.000	0.003	0.000		
Total	30.000	0.039			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*
Intercept	0.046	0.003	16.984	0.000	0.040
ACWI (0)	0.214	0.042	5.096	0.000	0.127
ACWI (-1)	0.268	0.048	5.623	0.000	0.170
ACWI (-2)	0.073	0.048	1.535	0.138	-0.025
ACWI (-3)	0.196	0.047	4.153	0.000	0.098
ACWI (-4)	0.147	0.046	3.168	0.004	0.051
ACWI (-5)	0.096	0.044	2.198	0.038	0.006
Total Beta	0.995				

To conduct this analysis, we run Equation 9 twice. In the first analysis, we set the dummy variable (D) equal to 1 when the public stock market performs positively, and 0 when the stock market performs negatively. We then calculate the size of the lagged betas. In the second analysis, we set the dummy variable equal to 1 when the public stock market performs negatively and 0 when the markets perform positively. Again we calculate the sum of the lagged betas.

If there is no behavioral bias in the pricing of real estate portfolios, then we would expect to see equivalent values of alphas and betas in both Up and Down markets. However, if there is a behavioral aspect of pricing real estate portfolios, the values would be different, indicating a bias to marking the real estate portfolio depending on whether the public markets were increasing or decreasing.

There are several reasons why real estate managers might be slower to mark down the value of their real estate portfolios in poor economic times and faster to mark them up in good economic times. It might be in their economic interest to pursue this form of managed pricing based on profit sharing incentives. In addition, real estate managers may not want to feel "left out" by stock market rallies—increasing the value of their portfolios more consistently when the financial markets perform well than when the financial markets perform poorly. Alternatively, real estate managers might want to mark up their values more quickly to take advantage of higher future sales prices, or stronger portfolio balance sheets. In sum, there are many motivating reasons why real estate managers might be more aggressive in marking up their assets and slower to mark them down in value. If this behavioral aspect is at work then we would expect the lagged betas to have less explanatory power in Up Markets. Conversely, in Down Markets, real estate managers might be slower to mark down the value of their real estate portfolios and might be more active in stretching out the effect of lower economic valuations. Therefore, in Down Markets we would expect to observe a larger explanatory power associated with lagged betas.

Our results are presented in Exhibit 4a and Exhibit 4b, which reflect two time periods—the full 21-year period and the last decade, respectively. Using the MSCI ACWI benchmark, over the full period, the total lagged beta in Up Markets is 0.69 versus 0.59 in Down Markets (see Exhibit 4a). Contrary to our hypothesis, these initial results would seem to indicate that real estate managers are slower to mark up their portfolios in Up Markets.

However, when we look at the results more closely we see that the R-Square measure for Up Markets is only 18% while it is 40% in Down Markets. This indicates that the lagged explanatory market variables have more explanatory power in Down Markets than Up Markets, consistent with our hypothesis. In addition, when we add up only those lagged beta variables that are statistically significant (p-values greater than 10%), we find that the Down Market Betas have more explanatory power than Up Market Betas—0.52 for Down Markets vs. 0.47 for Up Markets.

In addition, we observe a behavioral bias in the alpha intercepts. For the full period in Up Markets, the alpha is -0.09% while in Down Markets, the alpha is a positive 3.2%--another demonstration of the asymmetry in pricing in Up vs. Down Markets.

The results are more pronounced when we consider the last decade (see Exhibit 4b). Now the total lagged beta for Down Markets is 0.995 vs. 0.426 for Up Markets. In addition, the R-Square for Down Markets is 93% vs. 28% for Up Markets. Last, the alpha intercepts also display this behavioral asymmetry: -0.06% in Up Markets vs. 4.6% in Down Markets.

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These results support a consistent behavioral bias in the real estate markets. There is a clear predilection to price real estate portfolios relative to the public equity market much more slowly in Down Markets than in Up Markets. This is consistent with a desire by real estate managers to share more quickly in the tailwinds associated with positive results in the public equity markets.

Exhibit 5a and Exhibit 5b demonstrate similar results using the Russell 1000 benchmark. For the full period, in Up Markets, the total lagged beta is 0.35 vs. 0.55 in Down Markets and the R-Square is only 17% in Up Markets vs. 31% in down markets. For the last decade, the total lagged beta increases significantly in Down Markets—1.08 vs. 0.51 in Up Markets. The R-Square is also much higher in Down Markets—90% vs. 33% in Up Markets.

Last, reviewing the alpha estimates, we find results similar to those for the MSCI ACWI regressions. The alpha intercept is negative in Up Markets, but very large and positive in Down Markets. This is another demonstration of a behavioral asymmetry.

Our conclusion is that there is considerable asymmetry in the pricing in real estate portfolios. Specifically, there is a consistent bias by real estate managers to increase the value of their property values quickly when the public securities markets are performing well compared to when the public securities markets are performing poorly. This could very well be due to the economics of real estate management, an attempt to mark up values more quickly for future sales, or simply a desire by real estate managers to take credit sooner when the overall securities markets are performing well.

Another way to consider this issue is to review the alpha intercepts. Using both the MSCI ACWI and the Russell 1000 we found the alpha intercept to be negative in Up Markets and positive and very large in Down Markets. Is it reasonable to believe that real estate managers provide no excess return in Up Markets, but suddenly turn into star performers with significant alpha in Down Markets? We suspect that the answer is more about behavior and less about stardom. The truth lies somewhere in between, as demonstrated by the alphas in Exhibits 3a-3d.

4.4. Seasonal Beta Models

Another element to the lagged nature of appraisal-based valuations is that there can be a seasonal effect.[vi] It is possible that a greater emphasis is put on year-end appraisals than during the other quarters of the year. To test this theory we go back to Equation 9. This time we set the Dummy Variable equal to 1 for observed valuations at the end of the fourth quarter every year and 0 for every other quarter.[vii]

Exhibits 6 and 7 display our results. Compared to our initial lagged results, there is a much higher systematic beta component associated with year-end real estate values. For example, using the MSCI ACWI, Exhibit 6 shows a total lagged beta of 0.79 across the entire time period with an R-Square of 39%. Compare this with the results in Exhibit 3a where the lagged beta for MSCI ACWI was 0.57 and the R-Square was 37%. Interestingly, the alpha intercept does not change very much—1.1% in Exhibit 6 vs. 0.96% in Exhibit 3a. This indicates a seasonal bias to pricing real estate portfolios that captures more systematic risk than interim quarters.

When we look at the time period post the real estate bubble, the results are even more dramatic. The beta estimate for MSCI ACWI increases to 1.51 with an R-Square of 94%. Although, again, we find an increased alpha intercept for this time period in Exhibit 6 compared to Exhibit 3a.

Exhibit 7 confirms the patterns with similar results when using the Russell 1000. There are higher lagged beta estimates associated with December appraisals for both the full time period and for the post bubble period.

Exhibit 5a: Russell 1000 and Dummy Variables 1990-2011

Russell 1000: 1990-2011 UP MKT
SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.412
R Square	0.170
Adjusted R Square	0.090
Standard Error	0.025
Observations	81.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	7.000	0.009	0.001	2.133	0.051
Residual	73.000	0.045	0.001		
Total	80.000	0.054			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*
Intercept	-0.001	0.007	-0.102	0.919	-0.014
Russell 1000 (0)	-0.026	0.056	-0.455	0.650	-0.137
Russell 1000 (-1)	0.025	0.056	0.448	0.656	-0.086
Russell 1000 (-2)	0.078	0.055	1.422	0.159	-0.031
Russell 1000 (-3)	0.069	0.055	1.264	0.210	-0.040
Russell 1000 (-4)	0.108	0.055	1.964	0.053	-0.002
Russell 1000 (-5)	0.099	0.055	1.792	0.077	-0.011
Total Beta	0.354				

Russell 1000: Down Mkt 1990-2011
SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.560
R Square	0.314
Adjusted R Square	0.248
Standard Error	0.022
Observations	81.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	7.000	0.017	0.002	4.776	0.000
Residual	73.000	0.037	0.001		
Total	80.000	0.054			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*
Intercept	0.030	0.003	8.884	0.000	0.024
Russell 1000 (0)	0.082	0.054	1.515	0.134	-0.026
Russell 1000 (-1)	0.125	0.058	2.155	0.034	0.009
Russell 1000 (-2)	0.083	0.058	1.426	0.158	-0.033
Russell 1000 (-3)	0.121	0.059	2.058	0.043	0.004
Russell 1000 (-4)	0.076	0.055	1.386	0.170	-0.033
Russell 1000 (-5)	0.068	0.054	1.242	0.218	-0.041
Total Beta	0.554				

Exhibit 5b: Russell 1000 and Dummy Variables 2004-2011

Russell 1000: Up Markets 2004-2011
SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.577
R Square	0.333
Adjusted R Square	0.130
Standard Error	0.034
Observations	31.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	7.000	0.013	0.002	1.638	0.175
Residual	23.000	0.026	0.001		
Total	30.000	0.039			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*
Intercept	-0.007	0.013	-0.568	0.576	-0.035
Russell 1000 (0)	-0.114	0.144	-0.790	0.438	-0.412
Russell 1000 (-1)	0.009	0.144	0.060	0.953	-0.290
Russell 1000 (-2)	0.077	0.142	0.544	0.592	-0.216
Russell 1000 (-3)	0.145	0.132	1.097	0.284	-0.129
Russell 1000 (-4)	0.191	0.131	1.465	0.157	-0.079
Russell 1000 (-5)	0.201	0.131	1.536	0.138	-0.070
Total Beta	0.510				

Russell 1000: Down Mkt 2004-2011
SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.948
R Square	0.898
Adjusted R Square	0.867
Standard Error	0.013
Observations	31.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	7.000	0.035	0.005	28.893	0.000
Residual	23.000	0.004	0.000		
Total	30.000	0.039			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*
Intercept	0.049	0.003	14.582	0.000	0.042
Russell 1000 (0)	0.229	0.049	4.698	0.000	0.128
Russell 1000 (-1)	0.259	0.059	4.369	0.000	0.136
Russell 1000 (-2)	0.150	0.062	2.417	0.024	0.022
Russell 1000 (-3)	0.214	0.062	3.473	0.002	0.086
Russell 1000 (-4)	0.200	0.062	3.249	0.004	0.073
Russell 1000 (-5)	0.026	0.059	0.448	0.658	-0.095
Total Beta	1.078				

Also, while there is an increase in the alpha intercept post bubble, the alpha intercept remains constant across the full time period.

4.5. Asset Allocation Beta Models

Our last beta analysis relates to asset allocation models. Most asset allocation models use some form of mean-variance optimization to determine the optimal weights in which to blend asset classes into a total portfolio. In building a diversified portfolio, real estate is generally considered to be a good diversifying asset class with respect to public securities. But these asset allocation studies are typically designed to utilize the correlation coefficient between the current return stream of real estate and the current return stream of public market assets. As demonstrated above, a single period analysis is insufficient to determine the true relationship between the real estate markets and the public markets.

We run a simple experiment. We build an optimizer to determine the best mix of real estate when added to a traditional portfolio of stocks and bonds. In the first case, we use the one-period model to determine the level

Exhibit 6: ACWI December

ACWI December Lagged **1990-2011**

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.622
R Square	0.387
Adjusted R Square	0.337
Standard Error	0.021
Observations	81.000

ANOVA

	df	SS	MS	F	Significance F
Regression	6.000	0.021	0.003	7.776	0.000
Residual	74.000	0.033	0.000		
Total	80.000	0.053			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%
Intercept	0.011	0.003	4.119	0.000	0.006
X Variable 1	0.158	0.049	3.233	0.002	0.061
X Variable 2	0.155	0.049	3.158	0.002	0.057
X Variable 3	0.177	0.048	3.680	0.000	0.081
X Variable 4	0.155	0.048	3.216	0.002	0.059
X Variable 5	0.098	0.049	2.016	0.047	0.001
X Variable 6	0.049	0.049	1.002	0.319	-0.049
Total Beta	0.793				

ACWI December Lagged **2006-2011**

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.967
R Square	0.939
Adjusted R Square	0.912
Standard Error	0.011
Observations	24.000

ANOVA

	df	SS	MS	F	Significance F
Regression	6.000	0.032	0.005	40.894	0.000
Residual	17.000	0.002	0.000		
Total	23.000	0.034			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%
Intercept	0.013	0.002	5.706	0.000	0.008
X Variable 1	0.351	0.042	8.348	0.000	0.262
X Variable 2	0.338	0.043	7.868	0.000	0.248
X Variable 3	0.312	0.043	7.256	0.000	0.221
X Variable 4	0.233	0.043	5.426	0.000	0.142
X Variable 5	0.193	0.043	4.471	0.000	0.102
X Variable 6	0.086	0.041	2.103	0.051	0.000
Total Beta	1.512				

Exhibit 7: Russell 1000 December

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.577
R Square	0.333
Adjusted R Square	0.279
Standard Error	0.022
Observations	81.000

ANOVA

	df	SS	MS	F	Significance F
Regression	6.000	0.018	0.003	6.166	0.000
Residual	74.000	0.036	0.000		
Total	80.000	0.053			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%
Intercept	0.010	0.003	3.590	0.001	0.005
Russell 1000 (0)	0.121	0.050	2.412	0.018	0.021
Russell 1000 (-1)	0.147	0.051	2.896	0.005	0.046
Russell 1000 (-2)	0.167	0.049	3.375	0.001	0.068
Russell 1000 (-3)	0.153	0.049	3.100	0.003	0.055
Russell 1000 (-4)	0.097	0.051	1.916	0.059	-0.004
Russell 1000 (-5)	0.054	0.051	1.052	0.296	-0.048
Total Beta	0.739				

Russell 1000 December Lag **2006-2011**

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.934
R Square	0.872
Adjusted R Square	0.827
Standard Error	0.016
Observations	24.000

ANOVA

	df	SS	MS	F	Significance F
Regression	6.000	0.029	0.005	19.366	0.000
Residual	17.000	0.004	0.000		
Total	23.000	0.034			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%
Intercept	0.014	0.003	4.270	0.001	0.007
Russell 1000 (0)	0.289	0.055	5.228	0.000	0.172
Russell 1000 (-1)	0.319	0.059	5.419	0.000	0.195
Russell 1000 (-2)	0.297	0.059	5.049	0.000	0.173
Russell 1000 (-3)	0.227	0.059	3.848	0.001	0.102
Russell 1000 (-4)	0.181	0.060	3.034	0.007	0.055
Russell 1000 (-5)	0.110	0.060	1.832	0.085	-0.017
Total Beta	1.423				

Exhibit 8: Assett Allocation

	Single Period Optimum Weights	Multi-Period Optimum Weights
Real Estate	17.67%	8.68%
Public Equity	20.87%	19.45%
Bonds	61.45%	71.87%
Sum of Wts = 1	100.00%	100.00%
Risk Tolerance	0.50	0.50
Max Utility	1.74%	1.73%

of correlation between stocks, bonds and real estate. In the second case, we use the full multi-period analysis to determine the correlation of the real estate market with stocks and bonds. We place two constraints into our optimizer: 1) That the weights to stocks, bonds, and real estate be greater than or equal to zero--no shorting is allowed; and 2) That the sum of the weights allocated to stocks, bonds, and real estate be equal to one—the portfolio must be fully invested. We use a standard mean-variance utility function to conduct our analysis:[viii]

$$\text{Maximize Utility} = E\left[R_{portfolio}\right] - \frac{1}{2}\left(Risk\ Tolerance\right) \times \sigma^2_{portfolio} \qquad (10)$$

Exhibit 8 provides our results. We use estimates for risk, return and correlation for stocks, bonds and real estate over the full 1990-2011 period.[ix] The one difference between the utility optimizations is the correlation estimate of real estate with stocks and bonds. In the first optimization we use the single-period estimate of correlation between real estate and stocks and bonds. In the multi-period optimization we use the correlation estimates obtained in Exhibit 3a-3d.In the single period case, the weight to real estate is close to that of public equities at almost 17.7%. However, when the full correlation of real estate is used, the weight allocated to real estate declines by half to 8.7%. In the multi-period case, the weight of the portfolio allocated to public equities is reduced slightly compared to the single period model, because the reduced diversifying impact of real estate with public equities means that there must also be a reduction in the equity allocation. The surplus allocation flows into the bond portfolio.

This simple example demonstrates how portfolio allocation exercises can be skewed towards a much larger allocation to real estate when only a single-period market model is used. When accounting for the lagged systematic market risk embedded in real estate returns, the ability of real estate to diversify the investment portfolio diminishes significantly. Real estate still plays a significant role in the portfolio construction because it has favorable risk and return characteristics as an asset class. However, its diversification potential diminishes when a multi-period correlation estimate is used compared to stocks and bonds.

5. Conclusion

Real estate is a valuable asset class with a favorable risk and return profile. However, the value of real estate as either an alpha generator or a portfolio diversifier is potentially overstated. The reason for this is the illiquid nature of real estate that makes comparisons to contemporaneous financial market movements inappropriate.

Using a lagged beta analysis, we found that real estate is much more influenced by the publicly traded securities markets than previously thought. Using an expanded CAPM model we found that the overall beta of real estate to the public equity markets is many times greater than the single-period beta of about 0.04. Including lagged stock market returns as part of the systematic risk estimate greatly increased the sensitivity of real estate returns to the public stock markets. We found evidence that this lagging effect continues for up to five quarters of public market returns. We also found the lagged beta effect to be influenced both by real estate manager behavior and seasonality.

Concomitant with the increase in beta, we observed a decline in alpha or the excess returns derived from real estate. The decline in alpha was most noticeable when considering the behavioral aspect of lagged real estate betas—there was no measurable skill attributable to real estate managers in Up Markets, while there was large economically and statistically alpha in Down Markets.

Last, using a multi-period correlation coefficient, we found that real estate is not as large a portfolio diversifier as previously thought. This is perhaps the largest contribution of this paper as real estate has long been thought to be an ideal diversifying asset class from stocks and bonds. There is still value with real estate based on its own risk and return characteristics, but only about one half as much diversifying potential when a multi-period analysis is used.

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References

Anson, Mark. "Measuring a Premium for Liquidity Risk." The Journal of Private Equity, Spring 2010, pp. 6-16.

Anson, Mark. "Performance Measurement in Private Equity: Another Look." The Journal of Private Equity, Summer 2007, pp. 7-21.

Anson, Mark. "Managed Pricing and the Rule of Conservatism in Private Equity Portfolios." The Journal of Private Equity, Spring 2002.

Asness, Clifford, Robert Krail, and John Liew. "Do Hedge Funds Hedge?" The Journal of Portfolio Management, fall 2001, pp. 6-19.

Marcato, G., and T. Key. "Smoothing and Implications for Asset Allocation Choices." The Journal of Portfolio Management, Special Real Estate Issue, 2007.

Stefek, D. and R. Suryanarayanan. "Private and Public Real Estate: What is the Link?" The Journal of Alternative Assets, Winter 2012, pp. 66-75.

Woodward, Susan. "Measuring Risk for Venture Capital and Buyout Portfolios." Sand Hill Econometrics, May 2011.

Endnotes

i. It is worth noting that this simple one factor model ignores other risk factor exposures and attributes all of the a to skill rather than additional risk exposures.

ii. In our regression analysis, we tried different values of a and b. Eventually, we settled on a = 0.3 and b = 0.2. We also tried different (a, b) pairs including (0.40, 0.1) and (0.25, 0.25) and found no material differences in our results.

iii. This method has been applied successfully to hedge funds. See Asness, Krail and Liew (2001).

iv. We note that the Treasury bill returns in Equation 5 must also be lagged to coincide with the lagged stock or bond market returns.

v. Anson (2002, 2007) used the Thomson Reuters Venture Economics database to access private equity returns while Woodward (2010) used the Cambridge Associates database.

vi. This idea was suggested to me by Dr. Mark Wolfson of the Graduate School of Business at Stanford University.

vii. We tested every quarter but only found the seasonal effect associated with December appraisals.

viii. We keep our analysis simple and ignore the higher moments of the distribution of returns (skew and kurtosis).

ix. Another problem with the real estate market is that the appraisal process can "smooth" the returns associated with real estate and this dampens the risk. We use the method of Anson (2009) to unsmooth the return stream to get a better estimate of the volatility of real estate. Also, we use the same correlation for between the NPI and the Blackrock Aggregate bond index of 0.12; our regression analysis did not show any difference between the single and multi-period models.

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