Searching for a Common Factor in Public and Private Real Estate Returns

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Abstract

We introduce a methodology to estimate common real estate returns and cycles across public and private real estate markets. We first place REIT indices and direct real estate—NCREIF appraisal-based and transaction-based indices (NPI and NTBI)—on a comparable basis by adjusting for leverage and sector. We extract a common real estate factor, which is allowed to be persistent, from all these markets. Individual real estate indices load on this common factor and they also are driven by persistent, idiosyncratic shocks. The common real estate factor is procyclical and has low correlations with standard systematic factors. Short-run idiosyncratic deviations from the common real estate factor load on several capital market factors for REITs and on liquidity factors for direct real estate.

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1. INTRODUCTION

Are real estate investment trusts (REITs) and direct real estate ownership similar or different? On the one hand, both involve investing in physical buildings and land, which generate cash flows. Pagliari, Scherer, and Monopoli [2003, 2005] suggest that after adjusting REITs and direct real estate indices for leverage and sector composition, and also adjusting direct real estate returns for appraisal smoothing, REITs and direct ownership have similar risk and return characteristics. Other authors have shown there are important differences between REITs and direct real estate returns. For example, direct real estate transactions lead direct real estate appraisals, and there are significant lead-lag patterns between REITs and direct real estate returns.¹ Some of these differences persist even after taking into account the different sector and leverage composition of REITs and direct real estate returns.

We study the long-run commonality and short-run differences between REITs and direct real estate returns. Although REITs are securitized, REITs and direct real estate returns should be driven by common fundamentals in the long run since both involve ownership of real estate. Carlson, Titman, and Tiu [2010] develop a model based on different costs of capital in which public and private real estate markets move together in the long run, but in the short run, REITs and direct real estate price movements can diverge.

In the short run, REITs and direct real estate returns diverge through vehicle-specific shocks. Since REITs provide immediate liquidity and trade on centralized exchanges where other equities trade, they are exposed to systematic equity market factors. Clayton and MacKinnon [2001], for example, argue that REITs have significant exposure to value and small-cap factors. REITs are widely held and so may be buffeted by investor sentiment and noise traders, which DeLong, Shleifer, Summers, and Waldmann [1990], Hong, Scheinkman, and Xiong [2006], and others argue are significant influences on publicly traded stock markets. By contrast, direct real estate investing involves less frequent transactions and appraisal-based pricing tends to smooth returns over time. Direct real estate is then exposed to liquidity smoothing effects which do not affect REITs. Over the long run, these effects could cancel out, so that both REITs and direct real estate returns are exposed to the same common drivers and thus move together.

Our analysis proceeds in three parts. First, we follow Pagliari, Scherer, and Monopoli [2005] and Li, Mooradian, and Yang [2009], among others, and place REIT and direct real estate returns on a comparable basis so that they have the same leverage and sector composition. We refer to the raw REIT

¹ See, for example, Gyourko and Keim [1992], Barkham and Geltner [1995], and Oikarinen, Hoesli, and Serrano [2011].

and direct real estate returns adjusted this way as *comparable returns*. Unlike Pagliari, Scherer, and Monopoli [2005], we do not adjust for autocorrelations or volatility induced by the appraisal process. Rather, we preserve these idiosyncratic properties because they are specific to a particular index, and we wish to characterize how each index differs from the components that are common across REIT and direct real estate markets.

Second, we estimate a common factor across REIT and direct real estate returns using a latent components model. We filter the common real estate factor from the observed comparable REIT and direct real estate returns. The model attributes some portion of the movements of a particular real estate index as shared across all indexes, but some portion is specific to that index. Both the common and idiosyncratic components are allowed to be autocorrelated. Our estimation methodology handles different starting dates of each index.

Finally, we characterize the dynamics of the common real estate factor and examine how the index-specific components move relative to the common factor. This allows us to explicitly link the sources of difference between the common real estate factor and the underlying characteristics of the various real estate investment vehicles.

Our approach is related to a number of papers which investigate the lead-lag relationships between REITs and direct real estate, especially within cointegrated systems.² Our approach is different because we work directly with returns, which are $I(0)$, rather than with a total return index, which is $I(1)$. This makes our work comparable with the majority of finance studies which directly model returns. By assuming a factor model, we also impose economic restrictions on the sources of the shocks to each real estate market—that they must come from common sources or idiosyncratic sources. Thus, the main advantage is that our model highlights the common real estate factor and treats each real estate market as directly exposed to the common factor. Cointegration models, in contrast, employ an unconstrained covariance matrix and estimate a common trend by finding a linear combination of the $I(1)$ series that is stationary rather than decomposing common and idiosyncratic shocks.

Working directly with returns rather than $I(1)$ variables also makes our work similar to standard factor models such as the CAPM or APT and makes our model comparable to the earlier literature by Goetzmann and Ibbotson [1990], Giliberto [1990], and Ling and Naranjo [1999]. However, these authors do not allow for any persistence. In our model both the systematic and idiosyncratic components can be autocorrelated, and we empirically find that persistence is high for the common real estate factor and

² See, among others, Meyer and Webb [1994]; Geltner and Kluger [1998]; Pagliari, Scherer, and Monopoli [2005]; Hoesli and Serrano [2007]; Fuss, Morawski, and Rehkugler [2008]; Li, Mooradian, and Yang [2009]; Oikarinen, Hoesli, and Serrano [2011]; and Stefek and Suryanarayanan [2011]

the direct real estate idiosyncratic components. Thus, our model also captures the smoothing effects of Geltner [1991] and Ross and Zisler [1991], but allows the common and idiosyncratic smoothing effects to be estimated rather than needing to be directly observed.

2. DATA

We adjust the REIT returns to be comparable to direct real estate on the basis of sector and leverage adjustments following Pagliari, Scherer, and Monopoli [2003, 2005].

For publicly traded real estate, we take REITs from the CRSP/Ziman Real Estate Data Series. The CRSP/Ziman stocks are linked with CRSP for returns and with Compustat for financial statement data. As a starting point for publicly listed real estate returns, we construct a value-weighted index of REIT returns from this combined dataset. For privately held real estate returns, we use two indices based on data from the National Council of Real Estate Fiduciaries (NCREIF). The first is the appraisal-based Property Index (NPI). Appraisals are calculated based on factors that are already in place and are not instantaneous and are therefore lagging. The second is the NCREIF Transaction Based Index (NTBI), which is based on properties in the NPI that were sold.³

As of December 1980, there were 54 REITs with an aggregate market capitalization of \$1.8 billion in the CRSP/Ziman equity-only series, compared to \$1.9 billion in privately held properties in the NCREIF database. In the early 1990s, the number and market value of REITs as well as the market value of private market transactions increased dramatically. During the recovery from the savings and loan crisis of the late 1980s and early 1990s, the real estate industry recapitalized and investment in both REITs and direct real estate increased. The number of REITs peaked around 200 in 1998, and REIT capitalization reached a maximum above \$430 billion in 2007. The market value of the NPI posted a high close to \$340 billion in 2008. Since then, the number of REITs has fallen to 133 with a \$370 billion capitalization in December 2011, compared to \$280 billion in privately held real estate in the NPI and NTBI series.⁴

³ The NTBI is calculated in two stages. First, for all properties sold in the quarter, NCREIF calculates the average ratio of the sales price divided by the appraisal, lagged two quarters. Second, this ratio is multiplied by the NPI level, also lagged two quarters, to convert the result into the NTBI transaction-based price index. The lagged appraisal is used instead of the current appraisal because the appraisal price may be influenced by a subsequent sale within two quarters.

⁴ Source: Authors based on CRSP/Ziman and NCREIF data.

2.1 Leverage Adjustments

Although individual properties within the NPI and NTBI have leverage associated with them, NPI and NTBI returns are reported on an unlevered basis. REIT returns, on the other hand, represent the equity return of leveraged properties. During the past 30 years, REIT leverage—debt and preferred equity divided by enterprise value—has averaged 43%, and annual interest expenses have ranged from just under 6% to almost 9%.⁵

We delever the REIT returns to make them comparable to the NCREIF returns following Pagliari, Scherer, and Monopoli [2003, 2005]. Using the most recent balance sheet data on a monthly basis, we compute a leverage ratio for each REIT:

$$\text{Leverage Ratio} = \frac{\text{Debt} + \text{Preferred Equity}}{\text{Debt} + \text{Preferred Equity} + \text{Equity Market Capitalization}}, \quad (1)$$

where the equity market capitalization is computed using common equity, and we take book values for the preferred stock and debt. We compute an annualized interest cost per month for each REIT using the formula:

$$\begin{aligned} &\text{Interest \& Preferred Cost} \\ &= \frac{\text{LTM Interest Expense} + \text{LTM Preferred Dividends}}{\frac{1}{2}(\text{Debt}_{t-1} + \text{Preferred Equity}_{t-1}) + \frac{1}{2}(\text{Debt}_t + \text{Preferred Equity}_t)}, \quad (2) \end{aligned}$$

which takes the interest and preferred dividends paid over the last 12 months divided by the average amount of preferred equity and debt over the last 12 months. We use a one-year window to estimate the interest rate of debt to control for the effects of refinancing.

Using the leverage ratio and interest cost in equations (1) and (2), respectively, we compute a monthly delevered REIT return:

$$\begin{aligned} \text{Delevered REIT Return} &= \text{REIT Return} \times (1 - \text{Leverage Ratio}) \\ &\quad + \frac{\text{Interest Expense}}{12} \times \text{Leverage Ratio}, \quad (3) \end{aligned}$$

The delevered monthly REIT returns are converted to the quarterly frequency to match the quarterly frequency of the NPI and NTBI series.

⁵ Source: Authors based on CRSP/Ziman data.

Exhibit 1 shows that from January 1994 to December 2011, the raw REIT average return per quarter is 2.53%, with a standard deviation of 13.07%. Taking leverage into account lowers the average quarterly return to 1.14%, with a standard deviation of 5.15%. Thus, adjusting for leverage has a substantial effect on average returns and volatility—a crucial distinction between REITs and reported direct real estate returns.

EXHIBIT 1

Quarterly Returns, Standard Deviations, and Serial Correlations of Public and Private Real Estate

	Average Quarterly Returns				Quarterly Standard Deviation		Serial Correlation
	5 year	10 year	Since 1994	Available History	Since 1994	Available History	Available History
REIT	2.53%	3.96%	3.40%	3.46%	13.07%	11.51%	0.14
NPI	0.84%	2.01%	2.25%	2.06%	2.43%	2.22%	0.78
NTBI	0.62%	2.34%	2.74%	2.74%	5.74%	5.74%	-0.12
REIT (leverage adjusted only)	1.14%	2.37%	2.36%	2.71%	5.15%	4.79%	0.07
Comparable REIT	1.16%	2.38%	2.41%	2.78%	4.99%	4.51%	0.06
Comparable NPI	0.98%	2.19%	2.31%	2.28%	2.24%	1.98%	0.77
Comparable NTBI	0.47%	2.41%	2.64%	2.64%	5.49%	5.49%	-0.15

Note: Available history starts in Q1 1994 for NTBI and Q2 1980 for other series. All series end in Q4 2011.

Source: Authors based on CRSP/Ziman and NCREIF data.

2.2 Sector Adjustments

REIT and NCREIF returns have different sector compositions. REITs primarily fall into the four “core” real estate sectors of apartment, retail, office, and industrial, although other sectors are gaining representation.⁶ By contrast, given NCREIF’s institutional focus, NPI and NTBI include only the four core real estate sectors plus hotels. To place REITs, NPI, and NTBI on the same sector basis, we consider the four core real estate sectors without hotels.⁷ Retail REITs have the largest weight in the CRSP/Ziman REIT series. Apartment, office, and industrial REITs have stayed in 5%–10% bands around their current weights. Historically, office and retail have been the largest weights in the NCREIF indices. Retail

⁶ Historically at least 80% of the total REIT capitalization was in these sectors, but that weighting has fallen to about 60% in recent years as new sectors—including healthcare, data center, storage, timber, and others—have converted to REIT status and/or gained investor attention.

⁷ We also exclude hotels because of their small weight in the NPI—less than 5% at any time—and their relatively infrequent transactions.

gradually moved from the 40% in 1994 to 22% today as the supply of other property types grew much faster than retail, while some retail types—especially malls—moved into the REIT format.⁸

Exhibit 2 shows the sector composition of our core REIT and NPI/NTBI series as of December 2011. REITs are much more heavily weighted towards retail, at 46%, while the NPI/NTBI property-type mix is more balanced, with a 22% weight in retail. Offices, at 36%, account for a larger proportion of the direct property index, compared to the REITs weight of 18%.

EXHIBIT 2

REIT and NPI/NTBI Core Property-Type Weights as of 12/31/2011

Source: Authors based on CRSP/Ziman and NCREIF data.

To construct a *comparable REIT* return series, we weight monthly returns of REITs in the four core property types (apartment, retail, office, and industrial) by total capitalization (debt plus preferred stock plus equity). To construct the *comparable NPI* and *comparable NTBI* returns, we weight the quarterly NPI and NTBI returns for each property type and by the weights of each property type in the comparable REIT index.

Exhibit 1 also reports summary statistics of the comparable REIT, NPI, and NTBI series. Taking sector composition into account does not significantly change the returns from the delevered REIT series or the raw NPI and NTBI series. For example, the mean and standard deviation per quarter of the delevered REIT returns are 2.36% and 5.15%, respectively, from 1994 to 2011. Allocating the REIT series into the core property types changes the mean and standard deviation per quarter to 2.41% and 4.99%, respectively. Similarly, weighting the NPI and NTBI with the same sector weights as the core property

⁸ Source: Authors based on CRSP/Ziman and NCREIF data.

types in the REIT index has minor effects. For the NPI, the mean and standard deviation per quarter are 2.25% and 2.43%, respectively, in the raw series and 2.31% and 2.24% after accounting for sector weights. For the NTBI, the mean and standard deviation is 2.74% and 5.74% in the raw series and 2.64% and 5.49% after accounting for sector weights. Even though the REIT and the NCREIF series have different sector compositions, adjusting for sectors has a relatively small effect on these unconditional moments because all the series are diversified across several sectors. All these sectors are exposed to the same underlying economic drivers in the economy in the long run.

Exhibit 3 plots rolling two-year averages of the quarterly returns for all three comparable series and shows that they exhibit a large degree of comovement. Yet there are salient differences. The comparable REIT and NTBI series are significantly more volatile than the comparable NPI series due to differences in index construction, namely equity and transaction-based returns rather than appraisals (see also Exhibit 1). There are additional differences due to the timing of the real estate cycle and the economic environment. Generally speaking, the comparable REIT series seems to lead the comparable NTBI returns, which leads the comparable NPI returns. Because of instantaneous liquidity, the public markets are the most forward looking, followed by direct transaction markets, followed by appraisals. This is consistent with the findings of Gyourko and Keim [1992], Barkham and Geltner [1995], and others.

EXHIBIT 3

Returns to the Comparable Real Estate Series

Source: Authors based on CRSP/Ziman and NCREIF data.

Exhibit 3 shows that during the early 1990s, real estate fundamentals were poor and recovering from an oversupply of underlying properties. Very little capital was available to the real estate industry, and the public markets provided capital for the industry to recapitalize. The ability to buy assets in the public markets at favorable pricing helped REITs outperform the underlying property markets. During the late 1990s technology bubble, stock market investors were generally more focused on faster growing companies, while steady industries like real estate were out of favor. Despite moderate fundamentals at the underlying property level, the comparable REIT index underperformed the comparable NPI and NTBI indices. In 2008–2009, the lack of liquidity impacted all forms of capital-intensive real estate as available funding dried up. The overall message in Exhibit 3 is that the three series representing public and private real estate markets have large underlying comovements reflecting common exposure to the underlying economy. There are also important vehicle-specific idiosyncratic components. Estimating the relationships between our three series to extract a common, underlying real estate factor is the focus of the next section.

3. MODEL

We decompose a class of real estate, r_{it} , into exposure to a common real estate factor, f_t , and an index-specific component, g_{it} :

$$r_{it} = \beta_i f_t + g_{it}, \quad (4)$$

where β_i represents the loading of the real estate class, or investment vehicle, on the systematic real estate factor, f_t . We specify that the idiosyncratic component, g_{it} , is orthogonal to the common real estate factor, f_t .

The common real estate factor, f_t , follows:

$$f_t = c_f + \phi_f f_{t-1} + \sigma_f \varepsilon_t, \quad (5)$$

where $\varepsilon_t \sim N(0,1)$. The autocorrelation, ϕ_f , allows for persistence in the common real estate factor.

The dynamics of the real estate index component, g_{it} , follow:

$$g_{it} = c_i + \phi_i g_{i,t-1} + \sigma_i u_{it}, \quad (6)$$

which also allows persistence through ϕ_i . We set $u_{it} \sim \text{IID } N(0,1)$ to be independent of ε_t at all leads

and lags and also independent across series i .

Exhibit 4 illustrates the relation between the common real estate factor and the various real estate series. Since we model returns in equations (4)–(6), the index level can be interpreted as the cumulated return series. Movements in the real estate cycle correspond to the common real estate factor, f_t . As the model allows returns to be autocorrelated, it can capture the long swings in real estate markets documented by many authors (see, for example, Wheaton [1999]). The individual real estate markets, both public and private, follow the real estate cycle because they have exposure to the common real estate factor through the factor loadings, β_i . The larger the factor loading, the more that real estate market moves in sync with the real estate cycle, all other things being equal. The real estate indices do not exactly follow the real estate cycle due to shocks that are specific to the market segment. These shocks, g_{it} , can themselves follow their own cycles, which are captured through the ϕ_i terms. Since the persistence of the idiosyncratic real estate market movements may not be the same as the common real estate factor, the idiosyncratic cycles can partially offset, exacerbate, or sometimes completely cancel the effect of the common real estate cycle.

EXHIBIT 4

Common Real Estate Factor and Real Estate Series

For illustrative purposes only.

The model allows for rich patterns in matching lead-lag patterns through implied cross- and auto-correlations. For example, the cross-covariances of real estate market i and real estate market j are given by

$$\text{cov}(r_{it}, r_{jt-k}) = \beta_i \beta_j \phi_f^k \text{var}(f_t), \quad (7)$$

where $\text{var}(f_t) = \sigma_f^2 / (1 - \phi_f^2)$. The cross-covariances of a given real estate class i are given by

$$\text{cov}(r_{it}, r_{i,t-k}) = \beta_i^2 \phi_f^k \text{var}(f_t) + \phi_f^k \text{var}(g_{it}), \quad (8)$$

where $\text{var}(g_{it}) = \sigma_i^2 / (1 - \phi_i^2)$.

The model can be interpreted as a factor model where f_t is the common factor and g_{it} are idiosyncratic shocks specific to each real estate series. This makes our model similar to a CAPM or an APT as well as the models estimated by Goetzmann and Ibbotson [1990], Giliberto [1990], and others. However, there are two important differences: We allow for persistent common and idiosyncratic factors, and our common factor is latent.

Geltner [1991], Ross and Zisler [1991], and many others develop methods to “unsmooth” direct real estate returns. These methods implicitly involve modeling the private real estate return, which is the illiquid asset, with loadings on contemporaneous and lagged asset returns that are assumed to be liquid and have autocorrelations close to zero (see also Stefek and Suryanarayan [2011]). Standard smoothing filters assume that the loadings decrease in absolute value as the lags increase. A similar formulation is implied by our model. Since the common real estate factor, f_t , is persistent, we have:

$$r_{it} = k + \phi_f \beta_i \sigma_f \varepsilon_t + \phi_f^2 \beta_i \sigma_f \varepsilon_{t-1} + \phi_f^3 \beta_i \sigma_f \varepsilon_{t-2} + \dots, \quad (9)$$

where the ε_t shocks are i.i.d. innovations to the common real estate factor in equation (5). Thus, the exposure to a persistent real estate factor also induces smoothing in a particular real estate market. And the model also allows the possibility of autocorrelated market-specific deviations away from the common real estate factor.

We estimate the common real estate component, f_t , by a Bayesian Gibbs sampling algorithm, which we detail in the Appendix. The algorithm jointly estimates the common real estate factor and the parameters of the model.

4. EMPIRICAL RESULTS

4.1 Parameter Estimates

Exhibit 5 reports parameter estimates of the model. The common real estate factor has an average return of 1.89% per quarter. The common factor's high quarterly autocorrelation ($\phi_f = 0.69$) indicates the strong influence of past observations and reflects the cyclical, trending nature of real estate. Factor-loading betas above 1.0 for REIT and NTBI suggest that the market transaction-based vehicles have greater exposure to the real estate factor, while the appraisal-based NPI has much lower exposure ($\beta = 0.37$) to the real estate factor. Thus, market-based real estate transactions have greater exposure to underlying real estate trends.

EXHIBIT 5

Parameter Estimates

Common Real Estate Factor		Posterior	
		Mean	Std Dev
C_f		0.0189	0.0033
ϕ_f		0.6935	0.1212
σ_f		0.0153	0.0029

Factor Loadings		Posterior	
		Mean	Std Dev
REIT	β	1.2933	0.2734
NPI	β	0.3730	0.1025
NTBI	β	1.3337	0.2725

Idiosyncratic Returns		Posterior	
		Mean	Std Dev
REIT	c	0.0000	0.0002
REIT	ϕ	0.0013	0.0615
REIT	σ	0.0451	0.0039
NPI	c	-0.0026	0.0021
NPI	ϕ	0.5914	0.0862
NPI	σ	0.0140	0.0009
NTBI	c	-0.0001	0.0013
NTBI	ϕ	-0.3386	0.0844
NTBI	σ	0.0339	0.0030

Source: Authors based on CRSP/Ziman and NCREIF data.

The other model parameters reflect the series-specific idiosyncratic returns after subtracting the common real estate factor from the three series. After this adjustment, REIT returns have no autocorrelation ($\phi \approx 0$), which is expected for a public, forward-looking security, but the idiosyncratic standard deviation is relatively high at 4.51% per quarter. In contrast, the NTBI returns are negatively autocorrelated ($\phi = -0.34$). This may reflect the noise and sampling bias inherent in the series, as only a small fraction of properties trade during any given period (see comments by Goetzmann [1992]). We find that the autocorrelation of the NPI is still high ($\phi = 0.59$), even after adjusting for the common real estate factor, which is also positively autocorrelated. Such predictable and persistent autocorrelation reflects the smoothing inherent in returns that results from the appraisal process. This suggests a link to Cannon and Cole [2011], who find that appraisals are off by 12% on average from transacted prices and

lag prices in both rising and falling markets. According to Cannon and Cole, NPI appraisal error is systematic and has a macro influence. Our results show that the persistence induced by this process is even larger than the persistence from the general real estate cycle.

4.2 Common Real Estate Factor

Exhibit 6 plots the four-quarter moving average of the common real estate factor and the comparable series. By construction, the real estate factor is a composite of the three underlying series, yet it is not simply an equal-weighted combination of them. Rather, the algorithm allows each real estate market to have different factor loadings and places more weight on the REIT and NTBI series (see Exhibit 5). Our estimation is also able to extract the real estate factor in the early part of the sample even when the NTBI series is not available. The common real estate factor captures the underlying trend of generally positive quarterly returns in the real estate market during the past 30 years, with a slowdown in the late 1980s and early 1990s, extremely strong returns in the mid-2000s, and a steep decline in 2008–2009.

EXHIBIT 6

Returns to the Common Real Estate Factor and Comparable Real Estate Series

Source: Authors based on CRSP/Ziman and NCREIF data.

4.3 Common Real Estate Factor Innovations

We characterize how innovations to the common real estate factor move with macro, style, and liquidity factors, all at the quarterly frequency. We start with the returns of the equity and bond markets, proxied by the S&P 500 and Barclays Aggregate indices, to test for relations with the capital markets. Since the demand for real estate is also related to aggregate activity in the real economy, we include real GDP growth and the change in the Consumer Price Index (CPI). Finally, because real estate is a capital-intensive business, we also include a credit spread variable, the difference between the yield on BAA-rated corporate bonds and the yield on the 10-year Treasury. To characterize the real estate market from an investment-style perspective, we look at several standard style factors: SMB, HML, and MOM, respectively, which are the returns to small minus large cap stocks, value versus growth stocks, and momentum constructed by Fama and French [1993] and Carhart [1997].

We also consider two liquidity variables. The first liquidity variable measures liquidity in stock markets. Ibbotson, Chen, and Hu [2011] document that stocks sorted by turnover exhibit differences in returns. Similarly, we rank stocks in the Russell 1000 Index monthly by turnover—defined as shares traded divided by shares outstanding during the past 12 months—and then calculate the spread between the one-month forward returns of the lowest quintile minus the returns of the highest quintile. This low minus high turnover factor is the return to stock-level illiquidity. To measure the level of liquidity specific to the real estate market more directly using NCREIF data, we calculate the percentage of properties in the NPI that sold during a given quarter. These two factors have a cross-sectional correlation of only 0.02, suggesting that stock market liquidity and real estate liquidity are very different.

We regress innovations of the common real estate factor, which is defined as the innovation in equation (5) above, and report the results in Exhibit 7.⁹ In the multivariate regression, the common real estate factor loads positively and significantly on the S&P 500, indicating that it is procyclical. There is also a large negative coefficient on the credit spread, which is not surprising given that real estate is a capital-intensive asset class, and widening spreads are deleterious for the real estate industry. Real estate return innovations are linked to stock market and real estate liquidity, but in different ways. Real estate returns are negatively correlated with stock market liquidity. Consistent with Cannon and Cole [2011] and others, there is a strong positive relation between real estate returns and real estate liquidity.

⁹ In the univariate regressions, the common real estate factor also loads significantly and positively on SMB, but negatively on stock market liquidity.

EXHIBIT 7

Regression Results: Common Real Estate Factor

Common Real Estate Factor Innovations	Beta	P Value
S&P 500 Index	0.029	0.019
Barclays Aggregate	0.037	0.100
Change in Real GDP Growth	0.079	0.429
Change in CPI	-0.065	0.631
Change in BAA – Treasury Spread	-0.917	0.002
MOM	0.015	0.250
SMB	0.017	0.361
HML	0.019	0.238
Low Turnover – High Turnover	-0.001	0.923
NPI Turnover	0.172	0.004

Note: Coefficients in bold are significant at 5% level.

Source: Authors based on Haver Analytics and Bloomberg data.

4.4 Specific Real Estate Market Innovations

We construct specific real estate market innovations taking the residuals in equation (6). Exhibit 8 plots the two-year quarterly moving average of the innovations for each series. REIT innovations show the greatest variability around the common real estate factor, and tend to lead the innovations in the NPI and the NTBI. At turning points in the real estate cycle, REIT innovations move in opposite directions from NPI innovations, trending significantly higher or lower during real estate booms and busts in 1990–1994, 1998–2000, 2006–2008, and 2009–2011.

Exhibit 9 characterizes how real estate market innovations away from the common real estate market cycle move. We run multivariate regressions on the innovations in the real estate series using the same factors we used to analyze the common real estate factor.

We find that REIT innovations have several significant relationships with these exogenous factors, loading positively on the S&P 500 and Barclays Aggregate indices as well as SMB and HML. Based on this analysis, REITs provide investors with exposure to real estate through the common factor, as well as to other macroeconomic and capital market—especially stock market—factors. Our results refine the commonly held belief that REITs provide real estate exposure plus equity market exposure. These equity

market exposures are a potential source of opportunity for active managers of REIT portfolios in the short term.

EXHIBIT 8

Real Estate Series Innovations

Source: Authors.

EXHIBIT 9

Regression Results: REIT, NPI, and NTBI Innovations

Factors	REIT Innovations		NPI Innovations		NTBI Innovations	
	Beta	P Value	Beta	P Value	Beta	P Value
S&P 500 Index	0.234	0.000	0.007	0.630	-0.027	0.736
Barclays Aggregate	0.233	0.006	-0.019	0.520	-0.242	0.179
Change in Real GDP Growth	-0.054	0.884	0.049	0.702	-0.733	0.368
Change in CPI	0.306	0.541	0.009	0.959	-0.510	0.579
Change in BAA – Treasury Spread	-0.813	0.454	-0.883	0.019	-2.321	0.259
MOM	0.036	0.447	0.025	0.128	-0.130	0.165
SMB	0.289	0.000	-0.016	0.501	0.063	0.602
HML	0.155	0.011	0.024	0.253	-0.233	0.066
Low Turnover – High Turnover	0.038	0.316	-0.001	0.954	0.083	0.217
NPI Turnover	-0.273	0.218	0.239	0.002	0.196	0.632

Note: Coefficients in bold are significant at 5% level.

Source: Authors based on Haver Analytics and Bloomberg data.

NPI innovations load on two factors, credit spreads and real estate market turnover. We believe this offers several insights into the performance of the NPI: Increased activity in the physical real estate market leads to higher returns in the NPI, which suggests that the appraisal process is revised higher by transaction activity. And contrary to the standard belief that the NPI does not have strong correlations with the capital market, NPI innovations are affected by credit spreads, a capital market liquidity factor.

However, NTBI innovations have no significant links with any of our factors, possibly because superimposing a limited number of transactions in any given period over appraised values introduces sampling noise that may be obscuring the results. Yet it is notable that NTBI has weak negative correlations with all the factors except SMB and liquidity in both stock and real estate markets. The positive association with real estate market liquidity contrasts with this factor's negative—albeit insignificant—relation to REITs. While the statistical relation is insignificant, the coefficient on the credit spread is economically very large. This is intuitive. As financing becomes harder to obtain, appraisals should be lowered, which affects NTBI valuations.

5. CONCLUSIONS

Investors can get exposure to real estate through publicly traded REITs or private equity funds. While some assume that public and private real estate are separate asset classes and have different return and risk properties, we estimate a common real estate cycle across public (REIT) and private (NPI and NTBI) real estate markets. We find that this common real estate factor is highly persistent, reflecting the cyclical nature of real estate, and broadly exposed to procyclical market factors. Our model is able to capture idiosyncratic movements in vehicle-specific real estate markets away from the common factor. These innovations can also be persistent. Innovations in publicly traded real estate returns away from the common trend are correlated with equity and bond market returns, as well as capitalization and valuation metrics, implying that investing in public securities further increases exposure to other market factors. These capital market dislocations are a potential source of opportunity for managers of REIT portfolios in the short term. Innovations in private real estate returns away from common trend are positively correlated with capital and real estate market liquidity. Over the full real estate cycle, however, the effects of these different exposures largely disappear.

APPENDIX

The estimation is done by a Bayesian Gibbs sampling algorithm. The estimation allows for missing observations, since the NTBI sample is shorter than the NPI and REIT samples. The algorithm involves iteratively drawing the parameters and the latent factor from a series of conditional distributions, which in steady state yields the distributions of the parameters, the systematic factor, and the latent series-specific idiosyncratic factors. Missing observations are treated as latent factors and are also drawn in each iteration. A textbook treatment of Gibbs sampling procedures is presented by Robert and Casella [1999]. Similar estimations to equations (4)–(6) are done by Stock and Watson [2002] for a principal components model and by Ang and Chen [2007] for a stochastic beta and volatility model, among others.

We denote the parameter vector as $\theta = (c_f, \phi_f, \sigma_f, \beta_i, c_i, \phi_i, \sigma_i)$. We use the notation θ_- to denote the full set of parameters, less the parameters of interest. We denote the set of missing returns as $\{r_{it}^{unobs}\}$, the latent common real estate factor as $\{f_t\}$, and the full set of data by Y . We iterate over the following conditional draws:

Systematic Factor

We draw $p(\{f_t\} | \theta, \{r_{it}^{unobs}\}, Y)$ using the forward-backward algorithm of Carter and Kohn [1994]. Equation (4) represents a state equation and the returns in equation (5) represent a series of measurement equations in a Kalman filter system. We use the forward-backward algorithm of Carter and Kohn [1994] to draw the systematic factor. Note that when the missing returns are known, the measurement equations constitute a standard time-series panel.

Systematic Factor Parameters

Given the series of $\{f_t\}$, the conditional draw $p(c_f, \phi_f, \sigma_f | \theta_-, \{f_t\})$ is a standard regression and we draw these parameters using a standard conjugate normal-inverse gamma distribution. We assume a diffuse normal prior for ϕ_f which yields a normal posterior and an uninformative inverse gamma prior for σ_f which yields an inverse gamma posterior.

The full set of constants c_f and the real estate market-specific c_i parameters are unidentified. For identification, we assume that the latent factor mean is given by the weighted means of each real estate market return, where the weights are the factor exposures, β_i . We take the weighted averages only for the data which are observable at each point in time. Then, we use the AR(1) in equation (5) to infer out the parameter c_f from the unconditional mean of the latent factor.

Systematic Factor Loadings

We draw $p(\beta_i | \theta_-, \{f_i\}, \{r^{unobs}\}, Y)$. Equation (4) is a regression of index returns on the observable systematic factor $\{f_i\}$. This is a conjugate normal-inverse gamma draw. We require additional assumptions for identification given the small number of real estate series. First, we take an empirical Bayes approach using an initial estimate of the latent factor from an equally weighted average of the three real estate series. Initial estimates of the systematic factor loadings are obtained by standard regressions using equation (4). We set the prior mean, μ_β^p , to be the estimated coefficients and the prior standard deviation, σ_β^p , to be the Newey–West [1987] standard error estimate using four lags. The estimates are scaled so that the cross-sectional standard deviation across the betas is equal to 0.5, and this is maintained in all draws. Second, to ensure that no one series dominates and that the Kalman filter is well defined when the latent factor is extracted, we reject all draws falling outside a range given by four times the prior standard deviation around the prior mean, $[\mu_\beta^p - 4\sigma_\beta^p, \mu_\beta^p + 4\sigma_\beta^p]$. We use only data that are observable in drawing the betas.

Idiosyncratic Parameters

To draw $p(c_i, \phi_i, \sigma_i | \theta_-, \{f_i\}, \{r^{unobs}\}, Y)$, we note that given $\{f_i\}$ and returns, we can invert the idiosyncratic return, $\{g_{it}\}$, from equation (6). Then, equation (6) is a standard regression and we use a conjugate normal-inverse gamma draw. We take an empirical Bayes approach to estimating ϕ_i . Using the initial estimate of the latent factor, we can form an initial estimate of $\{g_{it}\}$ and estimate the parameters in regression (6). We specify the estimated coefficient and Newey–West [1987] standard error computed using four lags to be the prior mean and prior standard deviation, respectively. Occasionally, there are very large values of ϕ_i drawn for the REIT series—this is not a problem for the other series—and we do not update these values when this occurs. Specifically, we reject all values falling outside plus or minus four prior standard deviations away from the prior mean for the REIT series.

To identify the constants, c_i , we report them as market-specific constants around the common factor mean. This is done as follows. We draw the constant in the regression (5) and compute the real estate market unconditional mean. We calculate the market-specific mean by subtracting the mean of the latent factor. Using the AR(1) process in regression (5), we convert this back to a constant term, which is reported as c_i . Thus, all constant terms for the idiosyncratic real estate series parameters represent conditional mean movements around the common real estate factor.

Missing Returns

The missing return draw, $p(r^{unobs} | \theta, \{f_t\}, Y)$ involves simulating the idiosyncratic return, $\{g_{it}^{unobs}\}$, which follows an AR(1) process from equation (6). Note that $\{f_t\}$ in this step is observable, so the simulated idiosyncratic returns can be added to the systematic factors in equation (5).

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