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The MSCI Private Real Estate Factor Model

Research Notes

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Contents

Introduction

The rise in allocations to private asset classes has brought about two major challenges for asset allocation and risk management. The first challenge is the need to **put private assets on an equal footing with the total portfolio** to understand their contribution to total portfolio risk, and inform like-to-like capital market assumptions. The rise of the total portfolio approach (TPA) makes this all the more important.

The second challenge has been brought on as many investors explore a broader opportunity set in **global real estate.** Real estate investors who have traditionally had a **home bias** increasingly seek diversification and value abroad.

Both of these challenges point to the need for a risk modeling framework that is **broad in both asset class and geographic scope**. Traditionally, this has been limited by a lack of information. Private real estate valuations are scarce, and smoothing distorts the apparent risk and cross-asset-class correlations.

The MSCI Private Real Estate Factor Model consists of a suite of models and features:

- A Bayesian desmoothing methodology provides robust risk estimates from limited data sets
- Coverage spanning 31 countries across five continents
- A global property-type classification system allows like-to-like comparisons across markets
- Four hundred factors covering property type by region
- Coverage of farmland and timberland in the U.S. and U.K.
- Income return factors, distinguishing rental income from capital appreciation
- Property sub-type and metro area granularity in the U.S.
- Granular property sub-type factors in the U.K.

These features are incorporated into the MSCI Multi Asset Class Model, which spans global stocks, bonds, commodities, currencies, volatility futures, hedge funds and private equity.

The model looks at the three sources of real estate risk and return:

Debt + income return + capital appreciation

Modeling the first component, debt, is relatively straightforward, either as simple leverage or as funding instruments exposed to the risk factors of the MSCI Fixed Income Factor Models. The other two are far more challenging. Accurately modeling these components requires private real estate data, and statistical methodology that can see past the smoothness of the valuations.

The MSCI Private Real Estate Factor Model incorporates a global data set using a **Bayesian desmoothing** framework. In the big data era, modeling private assets requires "small data" techniques to make inference from scarce valuations. The Bayesian methodology enables a coherent synthesis of all sources of information, including public market returns, private asset valuations, peer group behavior and subjective economic relationships.

The Bayesian methodology also improves upon traditional techniques to desmooth private real estate valuations, by reducing noise and removing significant distortions. Standard approaches to desmoothing private asset valuations significantly improve on risk estimates based on the raw valuations. However, even these approaches tend to overstate the diversification benefits of private real estate. Our Bayesian methodology reveals a significantly higher level of commonality between private real estate and other asset classes.

Despite this commonality, however, the utility of other asset classes as proxies for private real estate is limited. Detailed tenancy and lease information has sometimes been misused to map real estate to equity and bond market factors.[1] These factors can be important ingredients in forming a view on a property's expected return, but they fail to capture the systematic risk in real estate.

With the use of granular private real estate data, it becomes apparent that some **intuitive relationships fail to have explanatory power**. The relationships between New York real estate and financial stocks, Houston and energy, or San Francisco and technology all have very low statistical significance, for example. The relationship between farmland and commodity prices is similarly weak.[2]

The MSCI Private Real Estate Factor Model helps investors understand the drivers of investments in global private real estate. It reveals a higher degree of commonality between public and private real estate, and shows real estate to be much less bond-like than others have assumed. Incorporated in the Barra Integrated Model, the MSCI Private Real Estate Factor Model brings private real estate investments into the same standards of risk management as the other 90% of the portfolio.

[1] We once read a paper (not cited) about a very detailed discounted cashflow model of private real estate that quoted predictions to four or five decimal places … and then came to the conclusion that more than 98% of the risk of an apartment building in Bucharest, Romania, could be captured with U.S. Treasury bonds.

[2] This may be due to a mismatch between the drivers of contemporaneous cash flows (local rents, or commodity prices), and the long-term expectations that factor into property values.

Methodology overview

In the absence of reliable market prices, investors look to a variety of information sources to understand private real estate:

- Appraisal-based valuations
- Listed real estate returns (e.g., REITs)
- Real estate transaction prices

Each of these can be useful, but alone each is insufficient.

Factor models are a powerful tool for synthesizing sources of information. They work by first breaking apart asset returns into contributions from systematic and asset-specific sources, then pooling information across many assets to understand the systematic factors.

The MSCI Private Real Estate Factor Model uses factors to bring together the three sources of real estate information to synthesize a “true” underlying property value. It models the property value by decomposing the return as

$$True\ Return = Leverage \times (Beta \cdot Public\ Proxy + Pure\ Private + Asset\ Specific)$$

Different information sources can be combined to model each component.

The table below highlights some of the advantages and disadvantages of each data source. Private real estate valuations and transactions are “faithful,” in that they reflect actual private real estate, including possible influences such as liquidity premia. In contrast, the returns of listed real estate include additional layers on top of the underlying real estate:

- Non-representative tilts and concentrations of the fund portfolio
- The management, skill and fees of the fund
- Different liquidity premia (paid versus earned)
- Possible noise from stock market flows and over-reactions

Different sources of real estate information have benefits and drawbacks

Information source	Benefits	Drawbacks
Appraised valuations	Accurate in the long run "Faithful"	Subjective in the short run Lagged Scarce Smoothed
Listed real estate	Timely Market-based	Misses liquidity premia Mismatched concentrations Fund management component Stock-market noise
Transactions	Market-based "Faithful"	Scarce Selection bias

Private real estate valuations and transactions have significant disadvantages, however. Transactions provide accurate, market-based asset prices, but each asset may go years or decades between transactions, and there can be selection biases in the transactions that occur that make them less representative of assets that do not transact. Accuracy is not useful if it comes only after a decades-long wait, and since real estate has such a large idiosyncratic component, it can be hard to make inferences from individual transactions.

Appraisals aim to shorten that wait by inferring the value of properties that have not changed hands from the prices of properties that have transacted. The time between observations is still measured in quarters, and the subjective valuations tend to be far smoother than market-based prices.

For the purposes of risk-forecasting, the smoothing can be the most difficult challenge. It not only blurs the picture, but can systematically distort the apparent risk, understating both the standalone risk and the systematic correlations of real estate.

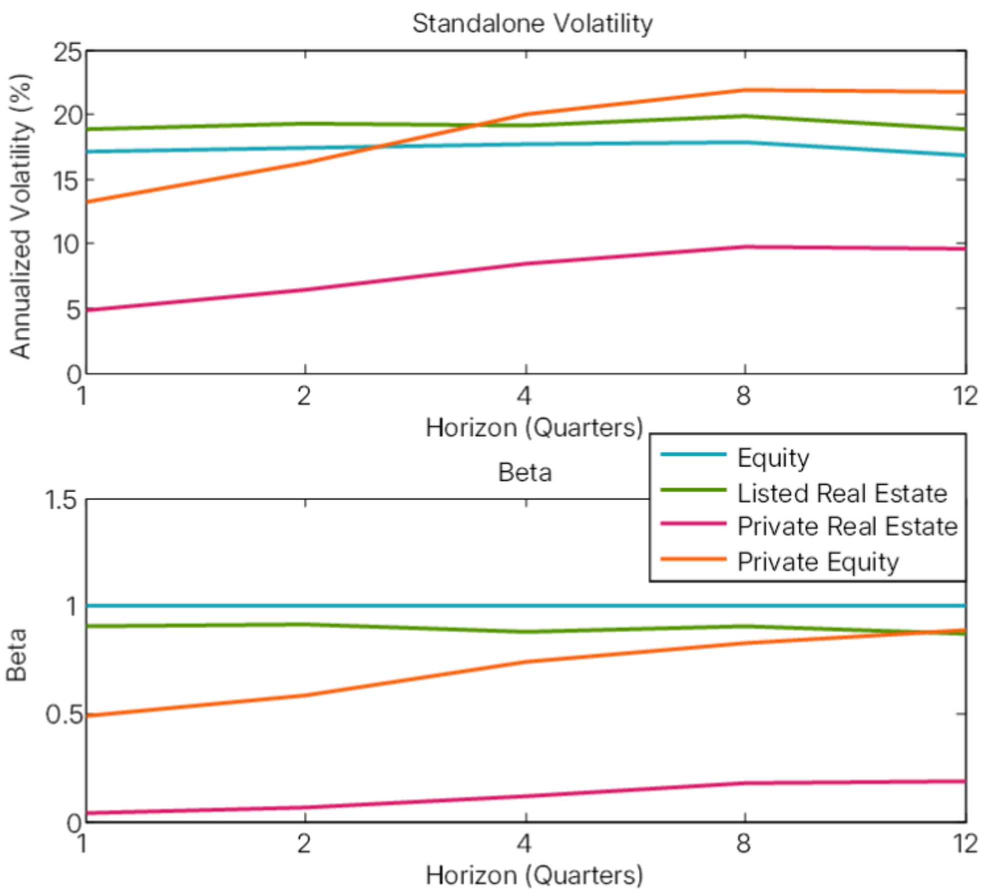
The chart below provides a demonstration of the distortions caused by appraisal smoothing. The figure compares the volatility and beta of private real estate valuations to other asset classes, over a range of return horizons.

In contrast with public equity, the low short-term risk rises steeply as the horizon increases: The valuations are flawed in the short term, but *eventually they converge* to the fair value, and reveal much higher risk levels.

The disconnect between the short-term and long-term behavior of the appraisals both demonstrates the problem, and points toward a solution. The long run convergence of valuation and fair value implies that accurate information is embedded in the appraisals, but we must work harder to extract it from beneath the layers of smoothing.

Geltner (1993) pioneered a **desmoothing** technique that makes this possible. By looking at differences between subsequent returns, Geltner showed how to back out the underlying "true" return to real estate. *Appendix A: Methodology details* reviews a new Bayesian desmoothing methodology that extends Geltner's approach to bring in more sources of information, and reduce noise.

Volatility and beta of private vs. public assets across horizons



The annualized volatility and beta of private assets rise significantly with the return horizon, in contrast with equity and listed real estate. A simple √T scaling to annualize the volatility leaves the public equity and listed real estate curves basically flat. However, the upward slopes in the private asset curves indicate that the short horizon returns are smoothed, and do not capture the true long-run risk of these asset classes. Note that Private Real Estate is unlevered, while the other time-series include leverage: the slope may be consistently compared across asset classes, but not the level of the curves. Source: MSCI, NCREIF

Although desmoothing can mitigate the distortions of the smoothed appraisals, it effectively results in only annual return observations.[3] Annual observations are useful for understanding the long-run risk of real estate, but on their own would lead to noisy and unresponsive estimates of risk. After the 2008 global financial crisis, for example, real estate might have looked like a low-risk safe haven for many months, until the first new data points arrived and demonstrated real estate to be closely linked to other risky assets in the market.

Alone, none of these views of real estate is sufficient to understand its risk, but used together the different sources of information can produce a single, coherent view. The MSCI Private Real Estate Factor Model synthesizes desmoothed appraisals, un-levered listed real estate proxies and — where available — transaction-linked indexes, to produce a better view into real estate risk than any one perspective provides.

The public proxy is constructed from unlevered listed real estate, and accounts for the property type and country of the property.[4] This component provides the primary link between private real estate and the public markets, and allows much more responsive estimates of changing private real estate risk from the behavior of the public markets.

The differences between listed and unlisted real estate are incorporated in two ways, with beta coefficients and "pure private" factors. These account for additional granularity in the property, and capture the illiquidity premia and other effects that differentiate private real estate from public real estate.

The pure private factors include income return, and subdivide property types by location. For example, the Canadian model factors distinguish the different behavior of offices in British Columbia, Alberta, Ontario, Quebec and the Rest of Canada. Additional factors in the U.S. and U.K. add further detail; a complete list of factors can be found in *Appendix C: Model coverage*.

The beta coefficients distinguish private real estate along the same dimensions as the pure private factors, reflecting differences in the relationship to the public proxy. For example, East Coast Offices in the U.S. tend to have a higher sensitivity to U.S. Office REITs than Midwest Offices, resulting in a higher degree of systematic risk.

Lastly, the asset-specific return reflects the large idiosyncratic component of property. For individual properties, the specific return can drive 50% of the total return, as discussed further in the section *Systematic drivers of returns: Specific risk*. Focusing on this is most important for assessing individual deals. But the importance of other components increases from the property to the portfolio to the total fund level. As properties are aggregated into a portfolio, the asset-specific components wash out and decline in importance, while less diversifiable factors take on greater importance.

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[3] This is true even if quarterly valuations are available, because of the seasonality of many appraisals. For more details, see the section *Methodology details*: *Bayesian desmoothing*.

[4] In some countries, there is little or no listed real estate in some sectors, and Bayesian thin-factor corrections are used to make inferences from the behavior of broader listed real estate, as discussed in *Appendix A: Methodology Details.* Public proxies are discussed further in *Appendix A: Methodology Details.*

Both a bottom-up, asset specific view, and the top-down factor view are important for understanding real estate. Neither is “correct” to the exclusion of the other, but each is relevant to different questions requiring different viewpoints.

The table below demonstrates the model in the context of a broad pension plan portfolio, contrasted with other standard views of real estate. The MSCI Private Real Estate Factor Model view represents a midpoint between the starkly different (and surprisingly commonplace) extremes of the public proxy and raw returns, showing alternatives to be both a source of systematic risk and a source of diversification.

In this example pension plan portfolio, real estate and private equity make up about 15% of the total weight. In the middle panel of the below table, the full Barra Integrated Model shows alternatives contributing 30% of the total diversification.[5] In the portfolios of many pension plans, alternatives contribute an even larger portion of the overall active risk.

If only public proxies are used to model the private assets, the standalone risk forecasts are similar, but the correlations appear to be much higher, and the diversification (and active risk) are much lower. Since diversification and active risk are among the main attractions to investments in alternatives, it is a significant weakness that the public proxy is largely blind to them.

The bottom panel shows a third approach, based on raw private asset valuations without accounting for smoothing. In this view, private asset appear to have much lower risk, and much lower correlations. The diversification from real estate is also low, for the same reason that cash is not a diversifier.

The MSCI model view represents a midpoint between the starkly different (and surprisingly common) extremes of the public proxy and raw returns, showing alternatives to be both a source of systematic risk, and a source of diversification.

[5] Diversification is defined as the difference between the total risk and the sum of the standalone risks. Diversification can be attributed to individual return sources with a generalization of the Correlated Risk Attribution (or X-sigma-rho) methodology.

Three approaches to modeling the risk of alternatives have starkly different implications

Public proxies	**Weight**	**Total risk**	**Correlation**	**Risk contribution**	**Diversification**
Total	100	8.0	1.0	8.0	1.6
Bonds	40	3.8	0.2	0.3	1.2
Public equity	40	14.5	1.0	5.7	0.1
Private equity	**6**	**17.2**	**0.9**	**0.9**	**0.1**
US real estate*	**10**	**10.8**	**0.9**	**1.0**	**0.1**
Hedge funds	4	4.8	0.8	0.2	0.0
MSCI model					
Total	100	7.8	1.0	7.8	2.0
Bonds	40	3.8	0.2	0.3	1.2
Public equity	40	14.5	1.0	5.6	0.2
Private equity	**6**	**22.0**	**0.7**	**1.0**	**0.3**
US real estate	**10**	**10.2**	**0.7**	**0.8**	**0.3**
Hedge funds	4	4.8	0.8	0.2	0.0
Raw valuations					
Total	100	6.5	1.0	6.5	2.0
Bonds	40	3.8	0.2	0.4	1.2
Public equity	40	14.5	1.0	5.6	0.2
Private equity	**6**	**10.2**	**0.4**	**0.2**	**0.4**
US real estate	**10**	**3.1**	**0.3**	**0.1**	**0.2**
Hedge funds	4	4.8	0.8	0.2	0.0

The top panel shows the contributions to risk of an example pension plan portfolio using public proxies for private assets; this view shows private assets providing little diversification. In the other extreme, the bottom panel shows risk for the same portfolio, based on raw private asset valuations without accounting for smoothing; this view shows alternatives having very low correlation and risk. The middle panel shows a balance between these two extremes; the risk according to the full Barra Integrated Model demonstrates that private assets are a source of both diversification *and* systematic risk.

Market insights

Is real estate a steady source of high returns with low risk and high diversification? Is real estate bond-like? Can real estate be proxied by the local economy? In the absence of data — and the appropriate tools to study it — any of these points of view could be used (and many are).

With the use of the MSCI Private Real Estate Factor Model, and the data and methodology underpinning it, the above questions can be put to the test empirically.

The results are quite stark. Our model finds that private real estate *is*:

- risky
- highly correlated with listed real estate
- highly correlated within countries
- highly diversifying across countries

Private real estate *is not*:

- bond-like
- equivalent to the stocks in the local economy
- highly diversifying within a country

These results challenge rules of thumb sometimes used to think about real estate.

The chart below shows the risk of different types of factors in the model. Two features are particularly striking. First, the differences in risk levels *among* countries are much greater than the differences *within* countries. This is the first indication of a strong *country effect* in real estate.

Many investors have looked to real estate as a substitute for fixed income, providing higher yields, and potential inflation protection. This may be a sound asset allocation decision, but it has important implications for risk management. Should the risk of real estate be managed the same as the bonds it replaced in the portfolio? Can the interest rate risk of real estate be used to hedge liabilities? Are the tenants a significant source of credit risk?

A second prominent feature of the below chart is that risk from the income component of real estate is dwarfed by the risk in the underlying capital. The steady income stream of real estate may be reminiscent of a bond's coupon stream, and some investors think of real estate as bond-like. If an office building in New York is leased to finance firms, the tenant's risk of default on the lease can be seen as a form of credit risk, perhaps leading to exposure to financial credit spreads.

This risk is real, but it is not the most important source of risk. An issuer defaulting on a bond destroys principal, while a tenant defaulting on the lease does not destroy the building itself (and if the lease is below prevailing rents, the tenant's default may actually be a good thing for the property owner). It may no longer be possible to rent out the building at the same rate, but this is reflected in the capital value, and is a reflection of the market, not the tenant. The most important source of risk in real estate is therefore uncertainty in the capital value, which has no analogue in bonds.

Risk by factor type

The risk of private real estate factors averaged by country and factor type. The low risk in the income stream indicates real estate risk is not primarily driven by bond-like behavior. The differences in risk between countries are much larger than the differences within countries, an indication of a strong country effect in real estate.

Another perspective into the bond-like behavior of real estate is provided in the chart below, which shows the correlation between broad real estate portfolios and interest rates in each country. Investment grade bonds have had a negative correlation with interest rates (prices went down when yields went up), but the typical correlation for real estate is close to zero. In many developed markets, the correlation is slightly positive, more similar to equity in these markets. The discounting of future cash flows is not the dominant source of interest rate correlation, but rather the correlation of expected cash flows. In many developed markets, this correlation has been positive: Interest rates have risen with expectations of growth, and fallen with a “flight to quality” when expectations for risky assets decline.

Correlation with interest rates

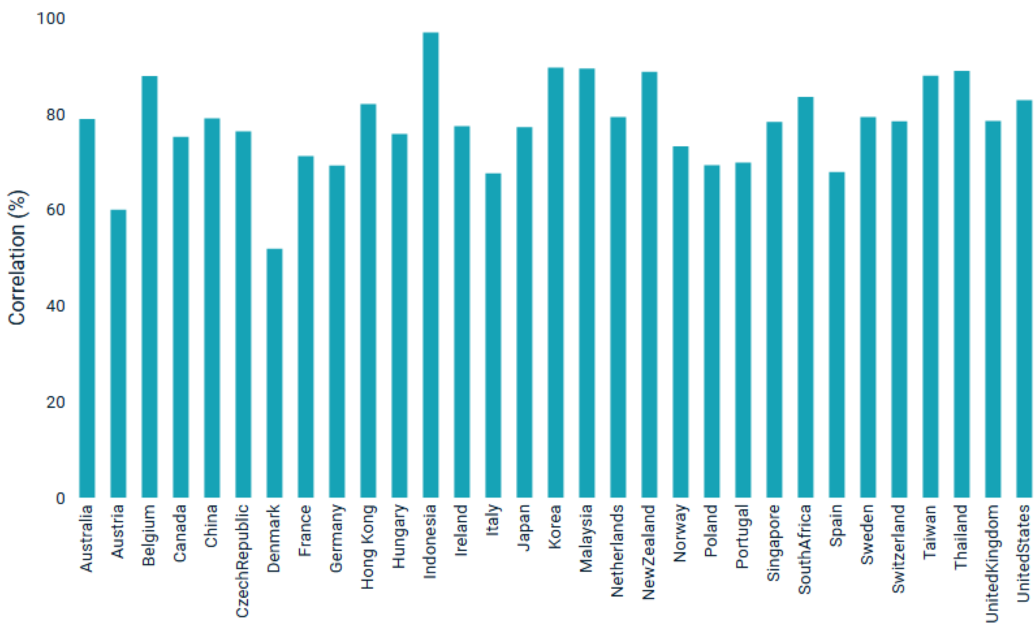
The correlation of broad private real estate with interest rates, country-by-country, is generally low. In many developed markets, the positive correlation has the opposite sign to bond returns, which move opposite to interest rates.

The high correlations between private and listed real estate shown in the chart below is another indication of the strong country effect in real estate. The public-private correlations visible in raw appraisals at the quarterly horizon are much lower: 25 to 35% is typical. Standard desmoothing techniques boost this correlation significantly, by roughly a factor of 2. However, as discussed in *Appendix A: Bayesian desmoothing*, even standard desmoothing tends to produce a downward bias in the correlation between public and private real estate. When this is corrected, the correlation increases further, in some countries into the range of 80%.

Such a high correlation between public and private real estate may be unwelcome news to those who see private real estate as strongly diversifying. However, it may not be surprising from an economic point of view. Listed and unlisted real estate are not identical, as discussed in the *Methodology overview* section, but their long-run returns are driven primarily by the underlying real estate cash flows they have in common. This is another indication of the strong country effect in real estate.

Although real estate is not strongly diversifying within a country, the following chart may offer hope to those looking for diversification in real estate. The correlation of real estate across markets is far lower than the correlation within markets, and also much lower that the corresponding correlations among equity markets. While the equity markets have become integrated over recent decades, global real estate remains fragmented. To investors able to overcome the (significant) operational obstacles, investments in global real estate represent a large, diversifying opportunity set.[6]

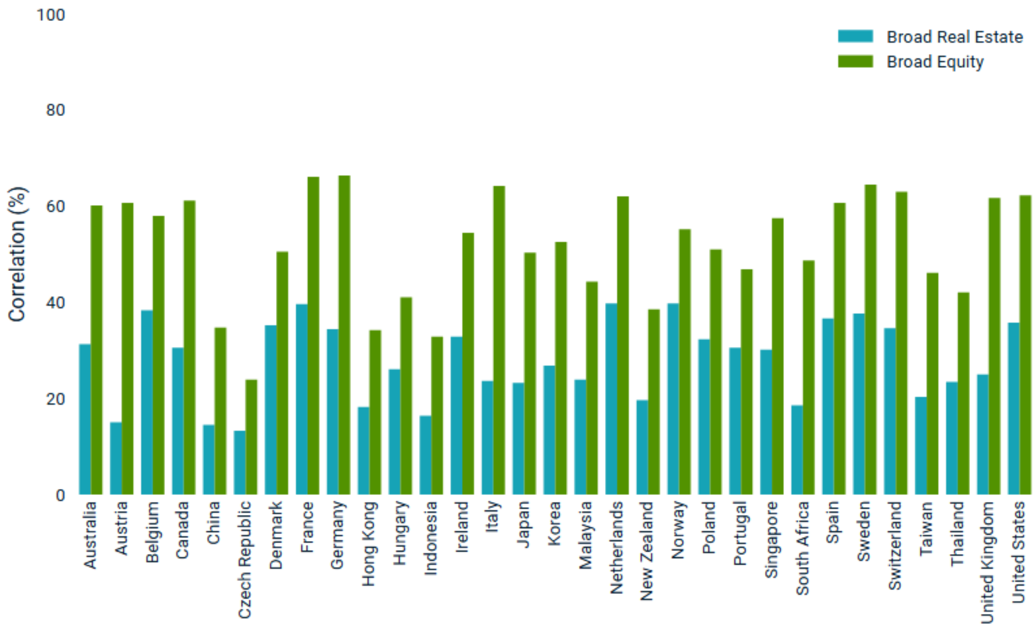
Public-private correlation



The forecast long-run correlation between listed and unlisted real estate is significantly higher than the smooth appraisals or even standard desmoothing would suggest.

[6] For more details, refer to “Crossing Borders to Diversify Risk with Real Estate” by Liu, et al. (2014).

Cross-country correlations



The average pair-wise correlations among broad country portfolios are significantly lower for private real estate than equity. For example, the U.S. real estate portfolio has an average correlation near 35% with the other country portfolios, in contrast with the 60% correlation of the U.S. equity portfolio. The lower correlations are a sign that global real estate is a much more fragmented market than global equity, and indicate significant opportunities for diversification in global real estate.

Lastly, the below table looks at the residual relationship between local real estate markets and dominant industries in those markets, net of the relationship derived from broader private real estate and public equity factors. Challenging the idea that real estate in these markets provides exposure to these industries — or could be proxied by them — the sensitivities are remarkably weak, even with the application of the full desmoothing methodology. New York real estate has had significant positive correlation with financial stocks, but this correlation is driven by the broader real estate and equity markets. Expectations for the local industries may play a prominent role in forming views on the *expected return* of a property, but the ability of specific equity sectors to explain or hedge local real estate *risk* is very low.

Local industries do little to explain local real estate markets

Private factor	Public industry	Beta
New York	Financials	0.0036
Boston	Financials	0.0017
Houston	Energy	0.0019
San Francisco	Technology	0.0024

Contrary to intuition, equity sectors do very little to explain local markets, net of the broader private and listed real estate markets. For example, New York real estate does have a significant correlation with financial stocks, but that correlation is driven by the broader real estate and stock markets. These factors may play an important role in forecasting expected returns, but local industries net of the broader markets capture little of the risk of local real estate.

Systematic drivers of returns

The old three rules of real estate, “location, location, location,” describe what may be the most important component of real estate returns, but in addition to location, the MSCI Private Real Estate Factor Model identifies other sources of commonality. “Location, property type, income, property-specific and leverage” does not have the ring of the old three rules, but it identifies the most important sources of return in a real estate portfolio.

In all markets except the U.S. and U.K. (whose additional granularity is discussed in the section *Systematic drivers of returns: Second tier factors in the US and UK*), the model starts by representing returns in the following general form:

Property Return = (*Type-by-Region Return* + *Income Return* + *Property Specific Return) x Leverage*

Leverage is accounted for on both ends of the model estimation. All return inputs into the model are de-levered, so the model factors represent unlevered real estate. Risk forecasts are subsequently built by applying the debt of an individual property or fund to reflect its particular leverage, or by explicitly modeling the funding instrument using the Barra Fixed Income Models.

As discussed in the *Methodology overview* section and *Appendix A: Methodology details*, the property-specific component of return can often contribute half of the overall risk and return at the property level, but this component rapidly diversifies in the context of the portfolio. The components that do not wash out are the systematic factors, based on income, property type and location, and are the primary drivers of return at the portfolio level.

These factors are discussed in the sections that follow, and the full set of factors is listed in *Appendix C: Model coverage*.

Property type and location factors

Location is important, but the effects of location are intertwined with the effects of property type.

A significant challenge faced by a global model of real estate is in the heterogeneity of property types across countries. There is tension between the need to capture the nuances of each market, and also to have common standards that allow comparisons across markets. How can we view “property type” so it is both tailored to each market, but also consistent across markets?

This challenge in private real estate is reminiscent of the problem of understanding differences among industries across global equity markets. The Global Industry Classification Standard (GICS®) helps resolve this issue with a hierarchy of industry classifications.[7] The standards are the same across markets, but the different levels of granularity allow customization to each market to capture what is most important to each.

[7] GICS is the industry-classification standard jointly developed by MSCI and S&P Dow Jones Indices.

The MSCI Private Real Estate Factor Model introduces a similar solution to the similar problem posed by comparing property types across markets: We developed a hierarchical segmentation of property types, with a common standard of increasing granularity to capture distinctions among markets. The table below shows the top two layers used in our model.

Global property types and property sub-types (US and UK)

Property types	Property sub-types
Retail	Regional mall
	Neighborhood convenience center
	Open-air shopping center
	Retail warehouse big box
	Other retail
Office	CBD office
	Suburban office
	Other office
Industrial	Logistics
	Self storage
	Other industrial
Residential	Urban residential
	Suburban residential
	Social housing
	Other residential
Hotels	
Other	

At the top level, six property types segment properties along the most important lines. The MSCI Private Real Estate Factor Model uses these six segments as the starting point in every market it covers, with further refinement along geographic and, in the U.S. and U.K. markets, property sub-type.

MSCI's local market knowledge played a central role in the further segmentation of property type into property type-by-location factors, as demonstrated in the table below. Statistical tests can help guide the tradeoff between capturing the most important details in each market, and the need for a parsimonious set of factors to guide forecasts of risk. However, statistical tests may miss the economic distinctions along which local participants view each market.

The factor sets of selected component models

Australia AUR1	Canada CAR1	Japan JPR1
AU Retail	CA Retail British Columbia	JP Retail Tokyo
AU Office Sydney	CA Retail Alberta	JP Retail Osaka
AU Office Melbourne	CA Retail Ontario	JP Retail Rest of Japan
AU Office Brisbane	CA Retail Quebec	JP Office Tokyo 5 wards
AU Office Canberra	CA Retail Rest of Canada	JP Office Rest of Tokyo
AU Office Rest of Australia	CA Office British Columbia	JP Office Kawasaki-shi Yokohama-shi
AU Industrial Sydney	CA Office Alberta	JP Office Nagoya-shi
AU Industrial Melbourne	CA Office Ontario	JP Office Osaka-shi
AU Industrial Rest of Australia	CA Office Quebec	JP Office Fukuoka-shi
AU Residential	CA Office Rest of Canada	JP Office Rest of Japan
AU Hotel	CA Industrial Ontario	JP Industrial
AU Other	CA Industrial Rest of Canada	JP Residential Tokyo 5 wards
AU Income Return	CA Residential	JP Residential Rest of Tokyo
	CA Hotel	JP Residential Osaka
	CA Other	JP Residential Rest of Japan
	CA Income Return	JP Hotel
		JP Other
		JP Income Return

Income return

With the exception of a handful of markets that have seen persistently large increases in property values, income is often the dominant source of return to real estate in the long run. Many investors have looked to real estate as a substitute for fixed income, providing higher yields, and potential inflation protection.

The steady income stream from real estate and the risk of tenants defaulting on the lease bear a resemblance to the coupon stream of a bond and its credit risk. Should risk management of real estate mirror that of fixed income?

To help answer this, our model introduces separate factors for the capital and income components of real estate returns. Typically, decomposing income factors does not significantly change the total risk forecast, but by breaking out the capital and income components, it can steer the focus of the risk management process. If the income return were a large source of risk, then the credit quality of tenants may be a primary focus of risk management, for example.

The chart below shows an example of quarterly income returns for segments of the U.S. market. Note the scale of the vertical axis: Over a 25-year history, the returns rarely venture outside of a 100-basis-point band centered around 1.5% per quarter.

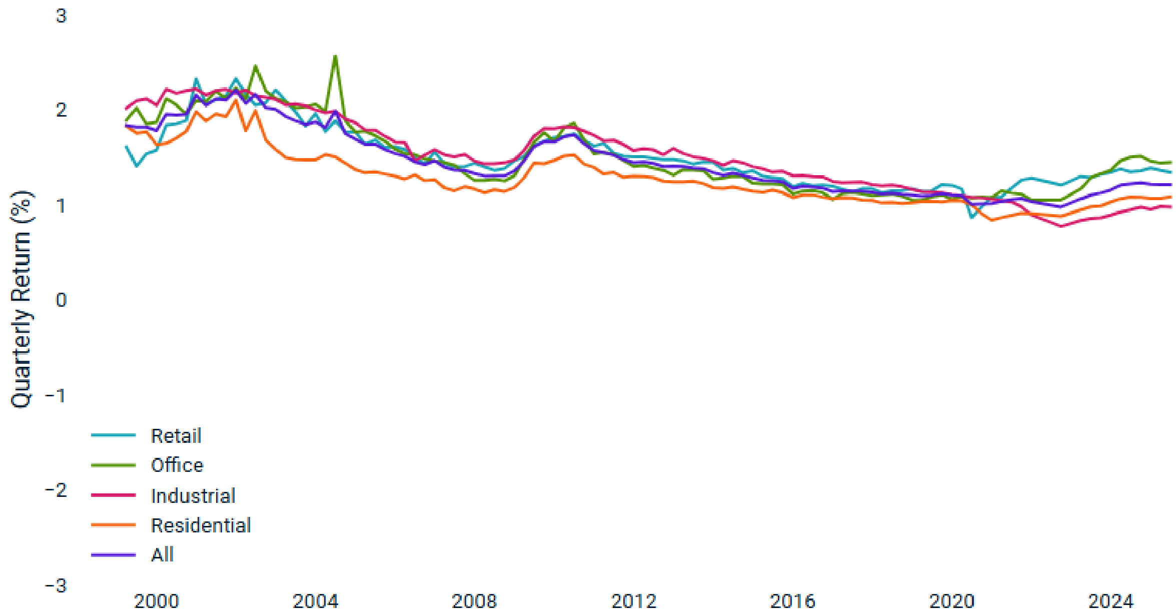
The steadiness of the income stream has opposite implications for return and risk. The steady positive returns accumulate period after period, adding up to what is often the dominant source of return in the long run, but a small source of risk.

In addition to being remarkably stable, the below chart also demonstrates that income returns are quite homogenous across segments of the market. With few exceptions, the small fluctuations in income returns are very similar across all segments of the market.

Due to both their low overall significance, and the high degree of homogeneity, income returns do not warrant additional factors to differentiate the risk of income return among different segments of the market. A single income return factor is used in each country to model the systematic risk in income returns.

The implications of the income return factors are discussed further in the *Market insights* section.

US income return



Income returns have been very stable, both across time and across segments of the market.

Specific risk

In addition to the systematic factors driving the returns of private real estate, a large component of the return of an individual property is idiosyncratic. This property-specific component is diversifiable; while it can be the largest source of risk in an individual property, it may be a small contribution to the risk of a broad portfolio.

Because the MSCI Private Real Estate Factor Model is primarily intended to model real estate in the context of a portfolio, its emphasis is on the systematic factors that do not diversify, more than the specific return that does. It measures specific risk in order to gauge the level of diversification in a portfolio, but it does not model all the characteristics that can distinguish one property from the building across the street. Those details are central to the property-level decisions that go into assessing individual deals, but they wash out among many assets.

In this sense, our model is complementary to the granular, bottom-up view of real estate that has been a strength of MSCI's data and analytics. Neither the bottom-up nor top-down view is "correct" to the exclusion of the other. Rather the two views capture what is most relevant to answering different sets of questions: *Should we purchase this property?* versus *How would this property contribute to the risk of the broader portfolio?*

We measure specific risk along four primary dimensions:

- Property-type
- Location
- Leverage

- Fund size

The chart below shows the property-specific risk in the U.K., as a fraction of the total risk, calibrated from a sample of 30,000 properties. This ratio is quite stable, near 50%, with respect to property type, time-period and return horizon. The higher ratio for the Other property type is to be expected: The greater heterogeneity among these properties leads to a lower fraction of return explained by the systematic factors.

These ratios are far more stable than either the numerator or denominator, which allows estimates of specific risk when property-level data is insufficient:

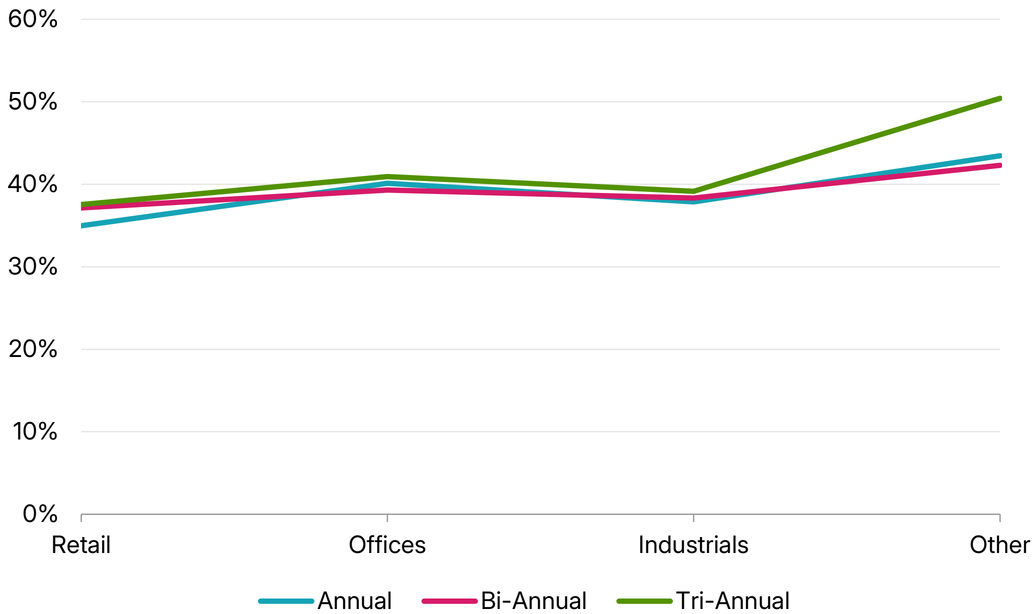
$$Specific\ Risk = \frac{Debt + Equity}{Equity} \times Fund\ Size\ Coefficient \times Property\ Type\ Ratio\ \times Factor\ Risk$$

Modeling specific risk and leverage at the individual property level provides more granularity, but the fund-size coefficient can be used to model real estate at the fund level, if property-specific information is unavailable. The coefficient reduces specific risk to reflect the diversification[8] that occurs within the fund's portfolio.

By linking to the factors, the specific risk forecasts give robust measures of diversification as the factor risk responds to changes in the markets. Further research could help gauge how risk levels differ among individual properties beyond the four primary characteristics, but the consistency with the factors is advantageous in the portfolio context, where it avoids distortions arising from different levels of responsiveness.

[8] The fund size coefficient is $1/\sqrt{N_{eff}}$, where the effective number of assets $N_{eff} = 1/\sum h_i^2$ is determined by the fund's weights h_i in each holding. If the fund holds equal weight in N properties, then $N_{eff} = N$. The product of the fund size coefficient and the leverage ratio define the specific risk scalar of each property or fund. For a discussion of modifications to the leverage ratio in the context of distressed or underwater properties, see *Appendix A: Methodology details*.

Property-specific risk



The property-specific risk as a fraction of the total risk is quite stable in the UK relative to property type and time horizon.

Second-tier factors in the US and UK

For the U.S. and U.K. markets, the MSCI Private Real Estate Factor Model provides additional granularity, with a second tier of factors for Property Sub-Type, and Metro Area in the U.S. (see the table below). These factors represent the return of the more granular market segments *relative* to the top tier factors. As refinements to the top tier, their use is optional: They can add detail if that is desired, but they can also be turned off if sufficiently granular holdings information is not available.

The second-tier factors are estimated with a cross-sectional regression[9] on the residuals of the top-tier factors, using the following return decomposition:

Property = *Type-by-Region* + *Income* + ***Property Sub-Type*** + ***Metro Area*** + *Property Specific*

Each second-tier factor captures a particular effect *net of* all the other factors. For example, the New York factor represents the return of New York City real estate relative to the broader region, and controlling for the effects of the property sub-type tilts of New York City, such as Central Business District (CBD) Office.

In addition to the factors for 13 U.S. Cities, the Metro Area factors also include four factors for the broader regions (ex the respective cities). For example, the "Rest of Northeast" factor absorbs the

[9] In the U.S., there is an exact multicollinearity between the sub-type and metro area factors, which is resolved by imposing the constraint that the cap-weighted average second-tier factor returns sum to zero.

difference in behavior of Northeast properties that are outside of the New York, Boston or Washington, DC, metro areas.

The metro areas and property sub-types of the second-tier factors in the US and UK

Metro area (US)	Property sub-type
Boston	Regional mall
New York	Neighborhood convenience center
Washington DC	Open-air shopping center
Atlanta	Retail warehouse big box
South Florida	Other retail
Dallas	CBD office
Houston	Suburban office
Chicago	Other office
Los Angeles	Logistics
SF Bay Area	Self storage
San Diego	Other industrial
Seattle	Urban residential
Denver	Suburban residential
Rest of Northeast	Social housing
Rest of South	Other residential
Rest of Midwest	
Rest of West	

Farmland and timberland models

In addition to standard real estate, we provide models of farmland and timberland for the U.S. and U.K. markets. The U.K. model consists of two broad factors for rural (farmland) and forestry (timberland), while the U.S. model has more granularity, as shown in the table below. The U.S. model looks at forestry, annual cropland (corn, wheat, soy, rice, etc.) and permanent crops (such as fruit and nut trees or vineyards), broken down by region, for a total of 15 factors.

Like real estate, market participants hold a variety of views on farmland and timberland. Some investors and asset managers view these assets as low risk and uncorrelated with the market, presumably based on the behavior of the smooth valuations. Others have attempted to proxy these asset classes with commodities, including somewhat exotic approaches to modeling timberland as an option on lumber.[10]

Although these approaches can be appealing, our model sees rather different behavior, once the smoothing is accounted for. The relationship between agriculture and commodities is weak, with typical correlations below 20%, for example. On the other hand, the standalone risk is relatively high, in the range of 8-14% on an unlevered basis, and the correlations with equity are also high.

The factors in the US and UK Agriculture models

UK Agriculture UKAG1	US Agriculture USAG1
GB Rural	US Forestry South
GB Forestry	US Forestry Northwest
	US Forestry Northeast
	US Forestry Lake States
	US Annual Crop Pacific West
	US Annual Crop Pacific Northwest
	US Annual Crop Corn Belt
	US Annual Crop Delta States
	US Annual Crop Southeast
	US Annual Crop Mountain
	US Annual Crop South Plains
	US Annual Crop Lake States
	US Permanent Crop Pacific West
	US Permanent Crop Pacific Northwest
	US Permanent Crop Lake States

[10] The option can be exercised by harvesting timber when lumber prices are high, or the timber can be left to grow when prices are low.

Conclusion

Global private real estate represents significant opportunities for investors, but also major challenges. When bond yields are low, many investors look to the income streams of real estate as a possible substitute for fixed income. The fragmentation of global real estate markets has resulted in low correlations, and large opportunities for diversification, in some ways reminiscent of global equity investing four decades ago.

However, the lack of liquidity and transparency in global real estate is also reminiscent of global equity decades ago. A lack of information and the smoothness of appraisal-based valuations have left investors and risk managers in the dark about the behavior of global real estate, or worse: A wide range of speculation is commonplace, including the view that real estate is a low-risk, high-return diversifier.

With the combination of proprietary data and a Bayesian desmoothing methodology, the MSCI Private Real Estate Factor Model makes it possible to shine a light on private real estate, and apply the standards of asset allocation and risk management that are applied to traditional assets.

Appendix A: Methodology details

Bayesian desmoothing

The challenges of private asset data require innovative econometric techniques to avoid drawing the wrong conclusions from smooth valuations, and to reduce the noise of small data sets. The MSCI Private Real Estate Factor Model uses a broad Bayesian desmoothing framework to address these issues.

The underlying mathematical and computational details can be challenging to work out, but the idea is simple: *What is our best estimate for risk, given what we know?* Bayesian statistics provide a framework to answer this basic question.

Bayesian techniques are often thought of as "shrinking to a prior," but there is much more to them. In addition to standard Bayesian shrinkage, Bayesian techniques can be used to derive a variety of statistical methods:

- *Thin factor corrections* remove biases from small sample sizes
- *Non-point estimates* address problems in combining noisy or uncertain parameters
- *Induced priors* systematically incorporate information from peer group behavior

In general, the purpose of the Bayesian methodology is to synthesize information and reduce noise, not to impose a strong view on the data. For example, the high correlation between listed and unlisted real estate is the result of properly accounting for the effects of smoothing, not a prior put in by hand. In the U.S. market, for example, the effect of priors has been to slightly *reduce* the beta of private real estate to public real estate.

A Bayesian approach can significantly reduce noise, even in the absence of a strong prior. Knowing only that the smoothing parameter must be between 0 and 1 can significantly improve the accuracy of its estimates, for example. Knowing that the estimated smoothing parameters are only estimates — with some inherent uncertainty — has a significant effect on the risk forecasts based on desmoothed returns. Incorporating the behavior of a peer group can yield an effective prior. All of these are benefits of a Bayesian approach that go beyond shrinkage toward prior information.

Often, the Bayesian approach leads to intuitive corrections, some of which have been applied by hand before. But rather than being ad hoc adjustments justified by intuition, they are instead derived from an explicit set of assumptions.

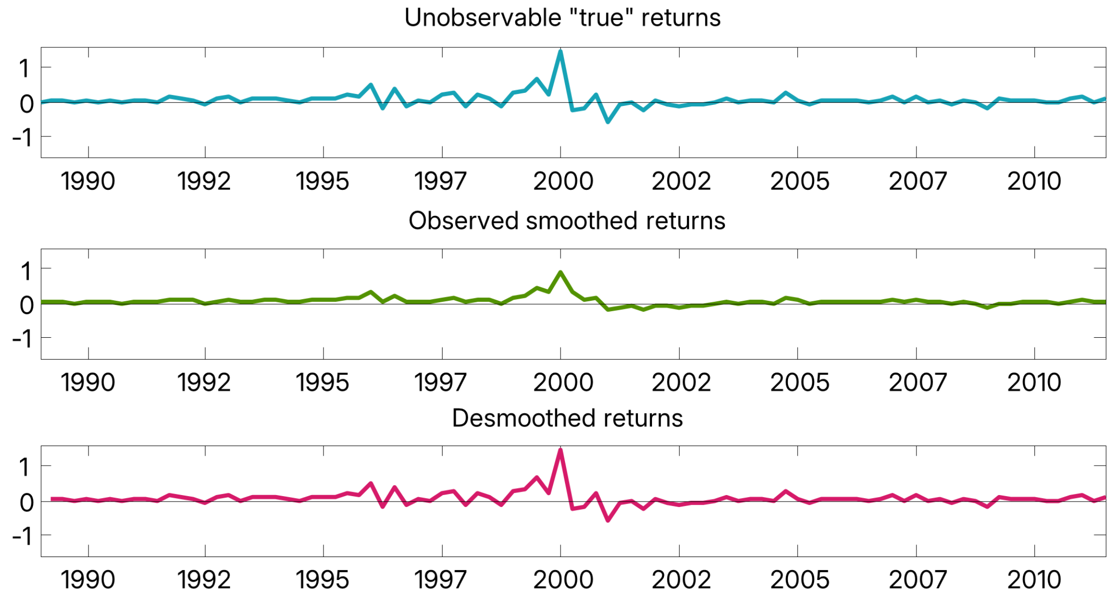
Desmoothing

The smooth behavior of real estate returns, as demonstrated in the chart *Volatility and beta of private vs. public assets across horizons*, is a consequence of market inefficiency. If it were possible to transact at the appraised values, a consistent profit could be made by buying after positive returns and riding the wave of similar subsequent returns.

However, real estate does not trade in an efficient market. Appraisals are a *valuation*, which may differ from the *value* that investors would actually pay for a property. Since no one is obliged to transact at the price of appraisal-based valuations, there is no arbitrage opportunity to close the mispricing.

To understand real estate, we must therefore distinguish the *observed return*, which is based on changes in valuations, from the *true return* reflecting changes in the actual value of a property.

Recovering true returns via desmoothing



Desmoothing can uncover the true returns from only observations of the smoothed returns. For this demonstration, the middle “observed” returns are simulated from a known “true” return, top. From observations of only the smoothed returns, the desmoothed returns almost exactly reproduce the true returns. In the real world, we have access only to smoothed returns, and cannot directly observe the true returns.

This difference between the observed and true returns makes it difficult to understand real estate. However, because the valuations eventually converge to the true value, the information must be in there somewhere. Geltner (1993) recognized that it is possible to uncover this information. He pioneered *desmoothing*[11] as a way to back out the return of the underlying true returns from observations of the smoothed appraisals.

In the simplest case, the smoothing of appraisals is governed by what is called an AR(1) process.[12] In this process, the valuation P does not track the true value V, but instead follows it in a game of catch-up. Each period, the valuation moves from its previous value P_{t-1} a fraction $(1-\lambda)$ toward the new true value V_t:

$$P_t = P_{t-1} + (1-\lambda)(V_t - P_{t-1})$$

[11] A note on terminology: To avoid ambiguity, we use the term “desmoothed” rather than “unsmoothed,” which elsewhere is sometimes used to refer to the raw, “not desmoothed” returns, and sometimes the opposite.

[12] AR(1) refers to an Auto-Regressive process with 1-lag.

The parameter λ is called the smoothing parameter. If the smoothing parameter is zero, then $P_t = V_t$: there is no smoothing. In the other extreme, if $\lambda = 1$, then $P_t = P_{t-1} = P_{t-2}$ ...: the valuation never moves from its initial level, regardless of the true value.

Even though we cannot observe the true value V_t, Geltner recognized that it's possible to reconstruct the true return r_t from the observed, smoothed returns s_t. To a good approximation,[13] the above behavior of the valuations leads to a corresponding relationship between the true returns and the observed, smoothed returns:

$$s_t = (1 - \lambda) r_t + \lambda s_{t-1}$$

This can be simply rearranged to find the true returns in terms of the observed returns:

$$r_t = \frac{s_t - \lambda s_{t-1}}{1 - \lambda}$$

Unfortunately, there are two significant obstacles to applying this simple form of desmoothing:

- Seasonality: The smoothing parameter is likely not a single number, but varies seasonally with differences in appraisal rates each quarter.
- Uncertainty: The smoothing parameter is not directly observable, but must be estimated.

Geltner desmoothing assumes the smoothing parameter is *constant*, and assumes it is *known*. The smoothing of a portfolio or index is likely to vary from quarter to quarter due to the seasonality of appraisals. Many properties are only appraised in the fourth quarter, for example, resulting in higher levels of smoothing in the first three quarters' returns.[14] Applying the basic desmoothing relation to quarterly returns would introduce distortions, and fail to reproduce the true quarterly returns.

The simple AR(1) smoothing process has been generalized to include additional lags in the relationship between true and smoothed returns, with AR(4) or MA(4) processes,[15] for example. The MSCI Private Real Estate Factor Model does not adopt these more complex multi-lag approaches, as they are poorly suited to seasonality in smoothing.[16] Instead, we base desmoothing on annual returns, even when quarterly returns are available. To take advantage of the additional data of quarterly returns, we use four different versions of the year: one year starting in Q1, one starting in Q2, and so on.

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[13] This approximation is corrected by higher-order terms in the returns, $\mathcal{O}(r^2)$...

[14] The lack of appraisals is likely not the only source of smoothing in valuations. We studied desmoothing of indexes for the time-dependent process $P_t = P_{t-1} + (1 - \lambda_t)(V_t - P_{t-1})$. If smoothing only arose from the valuations of properties not appraised, the smoothing parameter in each period would be related to the fraction of properties appraised a_t as $(1 - \lambda_t) = a_t$. However, the returns that result from desmoothing with this time-dependent coefficient still show a high degree of autocorrelation, which indicates that even when a property is appraised, the valuation is smooth, and doesn't reflect the true value.

[15] The AR(4) process generalizes the AR(1) process to 4 lags, $s_t = (1 - \sum_{l=1}^{4} \lambda_l) r_t + \sum_{l=1}^{4} \lambda_l s_{t-l}$. MA(4) refers to a Moving Average process with 4 lags, $s_t = (1 - \sum_{l=1}^{4} \lambda_l) r_t + \sum_{l=1}^{4} \lambda_l r_{t-l}$.

[16] These processes assume the lagged coefficients λ_l vary by number of lags l, but are constant over time. With seasonal smoothing, the contribution from a given lag would vary with both the time of year and the number of lags. A model that accounts for both many lags and seasonality would require fitting many parameters, making it less robust.

The use of annual returns in this way leads to more robust risk estimates. The details of the short-horizon behavior get washed out[17] at longer horizons. It is not necessary (or advantageous) to model the complexity of smoothing at the quarterly horizon, nor risk the errors that can arise from estimating many more model parameters.

The uncertainty in the smoothing parameter can be an important source of estimation error when using desmoothed returns to estimate risk. Since it enters in the denominator of the desmoothing relationship, uncertainty in the smoothing parameter can significantly skew the risk forecasts. For example, if a true smoothing parameter of .5 is mis-estimated as .75, the estimated risk will average more than twice the true risk.[18]

These issues highlight the importance of *robustness* of the methodology to the details of the underlying smoothing process. A desmoothing technique that would be optimal for one particular smoothing process can give skewed forecasts if the underlying smoothing is different. Rather than apply the desmoothing that is appropriate for the details of one particular smoothing process, it is better to use an approach that remains accurate over a range of possibilities.

In the context of an uncertain smoothing process, our research indicates that it is better to directly incorporate desmoothing into the risk-estimation methodology, rather than first building desmoothed returns, then applying standard risk techniques to the desmoothed time-series.

For example, a *single-step* regression estimates the smoothing parameters and beta coefficients together, in a single regression. In contrast, *two-step* demoothing first applies desmoothing to the private returns, and then subsequently estimates risk from the desmoothed returns. *Desmoothing and risk estimation simulation* shows the results of a simulation that explores these and other approaches to estimating risk from smoothed returns.

Intuitively, it is not surprising that single-step desmoothing can do better than the two-step approach. Looking only at the timeseries of private asset valuations, it can be difficult to resolve an ambiguity: Do periods of successive positive returns reflect smoothing in the valuations, or a bull run of positive true returns to the true value of real estate? Either interpretation could be consistent with the private asset returns, resulting in wide uncertainty in the smoothing parameters.

In single-step desmoothing, the returns of listed real estate can help resolve this ambiguity. Does listed real estate exhibit a similar run of positive returns? If so, the run of observed returns should not be interpreted as smoothing of valuations, but as the actual — if lucky — performance of the true value.

[17] In a phenomenon closely analogous to the Central Limit Theorem, long-horizon returns converge to an AR(1) process over a wide range of processes and lagging structures at shorter horizons.

[18] On average, the estimated variance would be greater than the true variance by a factor of 4.3.

Bayesian shrinkage

Many applications of Bayesian statistics take the form of *shrinkage*. An estimate based on observations is blended with a *prior,*[19] the best guess we had before we made the observations:

$$w \cdot Observation + (1 - w) \cdot Prior$$

The two points of view are blended with weights w determined by the relative size of the estimation error versus the uncertainty in the prior.

Bayesian statistics instruct us how to combine the information in the observations with the information we had before we made an observation. If the prior is tight, then we essentially knew the answer before making the observations, so the weight on the observations is small. Similarly, if the observations are noisy, they provide less information to move us from the prior. On the other hand, if the prior is only a rough guess, we put more weight on the observations, and more weight still as we gather additional information.

A basic example of Bayesian shrinkage is the Vasicek beta (see Vasicek (1973)). The standard estimate of a stock's market beta is by Ordinary Least Squares (OLS) regression of the stock's returns versus the market returns. The noise in this estimate is low if a long, stable history of returns is available.

If only a short return history is available, however, the OLS estimate can become very noisy, driven by coincidences in the returns in the sample, and produce beta estimates that defy common sense. The average beta of all stocks is 1, with most stocks falling in a relatively narrow range around the average. A beta of .6 or 1.4 is reasonable, but very few stocks should have beta less than zero or greater than two.

The Vasicek beta incorporates this "common sense," by blending the OLS estimate with the *prior* for beta that we would guess if we had no data to look at:

$$\beta_{Vasicek} = w \cdot \beta_{OLS} + (1 - w) \cdot \beta_{Prior}$$

Here the prior $\beta_{Prior} = 1$, and the weight w depends[20] on the noise in β_{OLS} relative to the tightness of our prior. If the estimation error is low, or we don't have much conviction in the prior, then $w \to 1$, and we put all the weight on the standard OLS estimate. However, if noise is large, the return observations provide limited information, and the best estimate puts much more weight on the prior.[21]

The Vasicek beta may seem intuitive, but perhaps *ad hoc*. Is that particular choice of weights the only good choice? In fact, the Vasicek beta is not ad hoc, but can be derived[22] from a Bayesian analysis:

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[19] The prior for a quantity x is a full probability distribution $P(x)$, not just a single value. However, sometimes "prior" is used as shorthand for the prior expected value, $E(x) = \int xP(x)dx$, which is the meaning here.

[20] The weight is $w = \frac{\sigma^2_{Prior}}{\sigma^2_{Prior} + \sigma^2_{OLS}}$, where σ_{Prior} is the width of the prior, and $\sigma_{\mathrm{OLS}}$is the noise in the OLS estimate, which is large if only a short data sample is available.

[21] If more information about a stock is known – such as industry membership, size, or other characteristics – the Vasicek prior can be refined considerably: This is one interpretation of factor models and "Barra betas".

[22] The Vasicek beta is the conditional expected value of beta given stock returns, Market returns, and a Gaussian prior: $E(\beta | r, R, prior)$.

What is the best estimate of beta, given what we know? Bayesian statistics provide answers to such questions in the form of *conditional expected values*:

What is the *best estimate*...	**→**	**What is the *expected value*...**
... *given* what we know?	**→**	***conditioned on* the data and priors?**

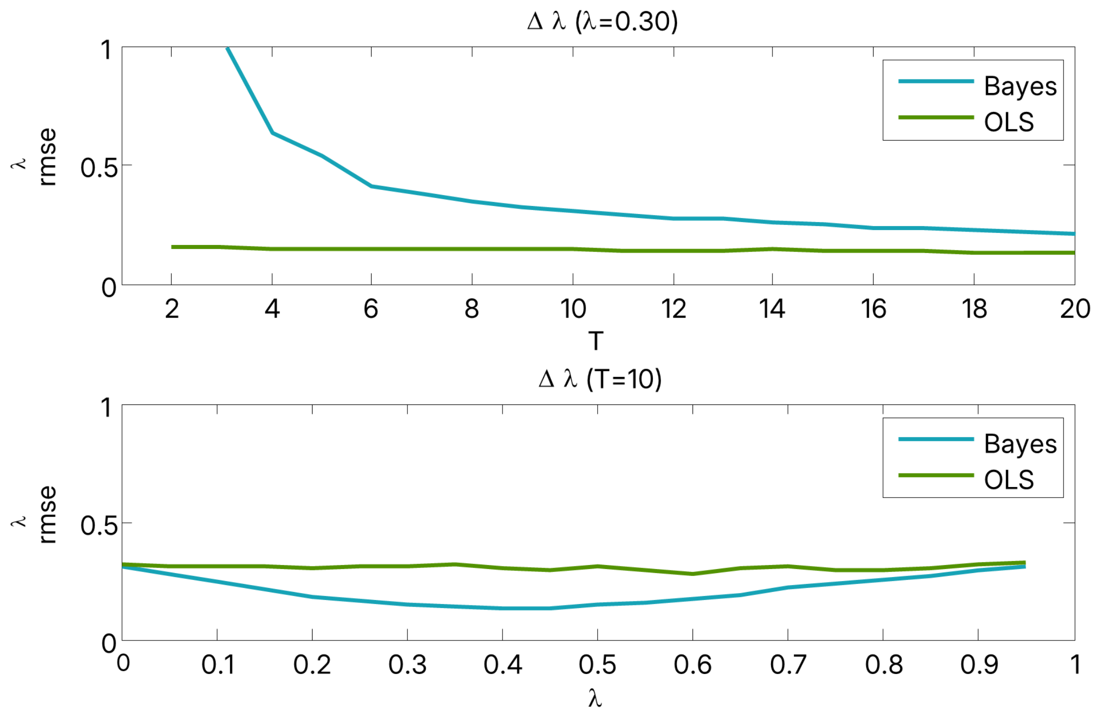
The shrinkage of the Vasicek beta is just one form that Bayesian expected values can take. In other cases, the Bayesian expected value cannot be solved so simply, and more advanced analytic and computational methods are required in practice.

Estimation of smoothing parameters is such a case. The form of the estimator is not the simple shrinkage of the Vasicek beta, but the idea is the same. In its simplest form, we ask: *What is the best estimate of the smoothing parameter, given return observations, and a uniform prior between 0 and .95.*[23]

The chart below shows the result of a simulation study of this simple Bayesian estimator, comparing the error in estimates of the smoothing parameter with the standard OLS estimator. The reduction in noise is very large for short histories, and still significant for data histories longer than 20 years. The improvement is extended significantly when additional effects are taken into account: induced priors, thin factor corrections, and the single-step regression with listed real estate.

[23] A smoothing parameter above .95 would be very extreme. The timescale for the appraisal to absorb a change in the true value is roughly$1/(1-\lambda)$. A smoothing parameter over .95 implies a timescale of more than 20 years. A more realistic upper bound is lower, perhaps .8, corresponding to a 5-year time scale for appraisals to catch up to true values.

Estimation error in Bayesian vs. OLS



The estimation error for the smoothing parameter is significantly reduced in a Bayesian approach, even in the absence of a strong prior, relative to the standard Ordinary Least Squares (OLS) estimator. In this simulation study, estimation error is measured as the Root Mean Squared Error (RMSE) between the estimate and the true value. The top panel looks at estimation error as the number of return observations is varied up to 20 years, and the bottom panel looks at different "true" values of the smoothing. Even though the prior is very weak — the smoothing parameter is assumed to be anywhere between 0 and .95 — the benefit is large.

Non-point estimates and thin-factor corrections

A common approach to estimating risk from smoothed time series proceeds in steps:

I. Estimate the smoothing parameter

II. Estimate the desmoothed returns

III. Estimate risk from the desmoothed returns

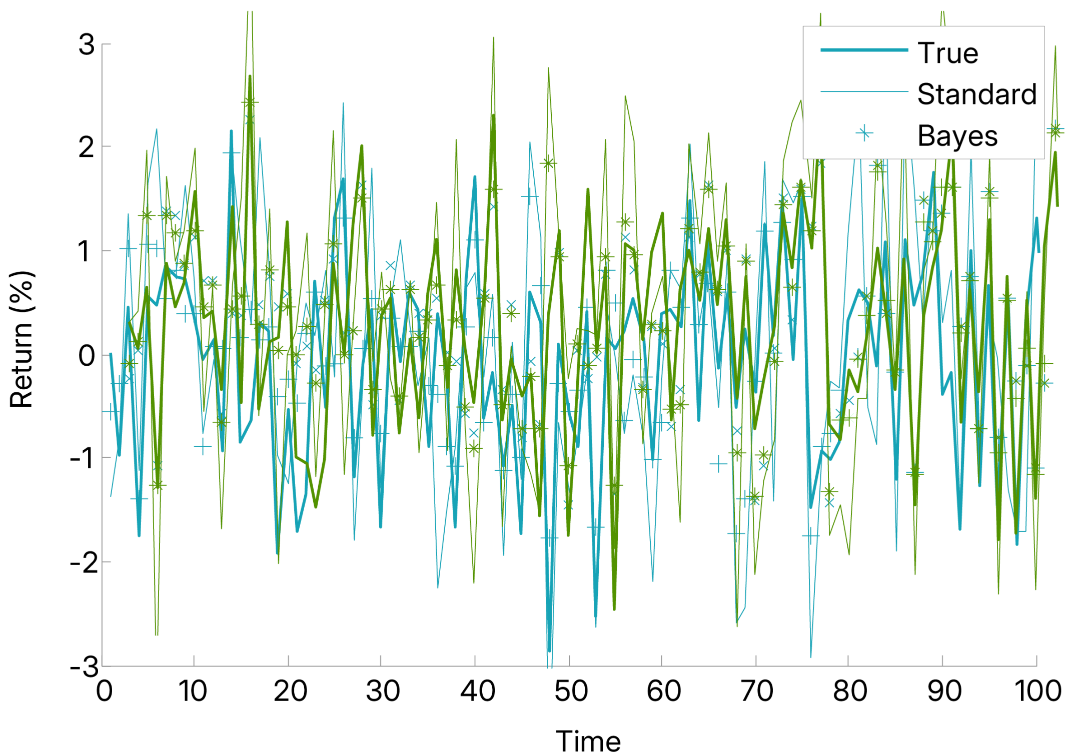
While each step involves an uncertain *estimate*, it is passed on to the next step as a single number — a "point estimate" — which is used as if it were *known*. Errors in the smoothing parameter can have a large effect on risk forecasts, and these errors are skewed: errors in smoothing can lead to arbitrarily large risk forecasts, but risk cannot be less than zero. Does this lead to a tendency to over-forecasting risk? Is there any way to improve the risk forecasts, taking into account the uncertainty of the ingredients along the way?

Bayesian methods allow us to account for this uncertainty naturally. Rather than the three steps above, there is a single step:

I. Estimate risk from the smoothed returns, given priors on the smoothing parameters

The mathematical form of the Bayesian estimate is discussed in the footnote.[24]

Simulation of thin factor returns: OLS vs. Bayesian estimates



A simulation of "thin factor" returns: The two solid curves show the true returns of two highly correlated factors. The dashed curves show standard Ordinary Least Squares (OLS) estimates of these returns taken from small samples of assets. The noise in the small sample inflates the volatility of the factors, and significantly reduces their correlations. A Bayesian estimate of the factor returns uses only the same information as the OLS estimate, but is much more accurate. However, even with the improved estimates of the returns, the best estimate of risk is not taken from this point-estimate of returns, but includes further modifications.

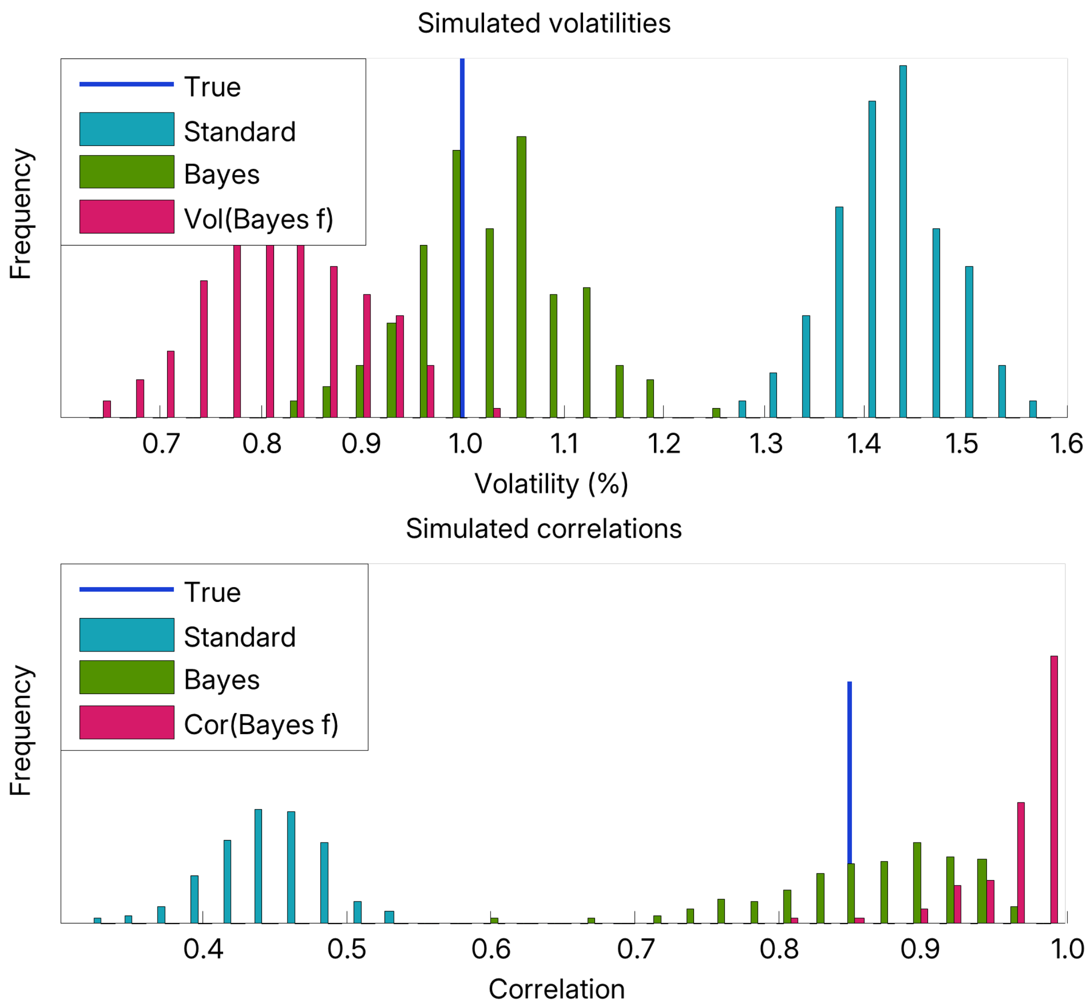
[24] An example of a Bayesian estimate of beta that accounts for uncertainty in the smoothing parameter is

$$E(\beta|s,R,priors) = \int d\beta d\lambda dr \cdot \beta \cdot P(\beta,\lambda,r|s,R,priors)$$

Here the joint probability $P(\beta,\lambda,r|s,R,priors)$ incorporates the posterior uncertainty in beta, the smoothing parameter λ and the true returns r, conditional on the observed smooth returns s, market returns R, and any priors, such as $0 \leq \lambda \leq .8$. Evaluating the right-hand side is computationally difficult, but conceptually straightforward.

Another important example of non-point estimates arises with *thin factors*, which are estimated from a relatively small number of assets. The small sample size can contribute to large noise in the factor return estimates. If this uncertainty is ignored, it can lead to exaggerated risk forecasts, and under-forecast correlations.

Risk estimates from OLS vs. Bayesian forecasts



Estimates of risk for the "Simulation of thin factor returns: OLS vs. Bayesian estimates." The small sample size not only adds noise, but introduces large biases in the standard OLS estimates. Even applying standard risk estimates (volatility and correlation) to the improved Bayesian estimated factor returns (Bayes f) does not eliminate the biases. The best estimates of risk use not only the best estimate of returns, but also incorporate the uncertainty in the return estimates (as in the Bayes risk forecasts). The Bayes forecasts do not eliminate noise altogether, but they are far more accurate than the alternatives.

For example, consider estimating the risk and correlation of two broad markets, but imagine that we were restricted to looking at only a handful of stocks in each market. How does the risk estimated from the small sample compare with the true risk in the broad markets? The above chart shows a simulation study where the true broad market returns are generated with a high degree of correlation, but they are estimated from a small subset of the market.

The Ordinary Least Squares (OLS) estimated returns are much more volatile, and much less correlated than the true returns. Using this estimate could give the impression that the two markets have much more idiosyncratic return than they do. In contrast, a Bayesian estimate of the factor returns, based on the same information as the OLS estimate, is much more accurate, even without any prior.

However, even with the improved estimates of the returns, the best estimate of risk does not just take the covariance of the point-estimate of returns:

$$Estimate(Risk) \neq Risk(Estimate)$$

Rather, the Bayesian risk estimate produces further thin-factor corrections. The result of these corrections is shown in the following chart, which compares the standard risk forecast to partial and full Bayesian approaches. In the standard approach, noise in the return estimates exaggerates the volatility and understates the correlations. The partial Bayesian approach, which builds standard risk estimates from the improved estimates of return of the previous chart, is also somewhat biased, in the opposite way.

The full Bayesian risk estimates[25] use not only the best estimate of returns, but also incorporate the uncertainty in these return estimates. This non-point estimate of risk does not eliminate noise altogether, but is far more accurate than the alternatives.

In the context of real estate risk, the effect of small sample size can be large. Individual property returns are very idiosyncratic, which can introduce large noise levels when market returns are estimated from smaller samples of properties.

The induced prior

In some cases, we don't have strong priors on a quantity of interest, but we can construct an effective prior from the distribution of a peer group of related observations. Before looking at *any* data, for example, we may not have a strong opinion about the smoothing parameters of the US real estate market. But once we have looked at returns for many different segments of the US market, we would not expect the smoothing parameter of the next segment to be vastly different.

In *Appendix A: Methodology details,* we saw shrinkage estimators that primarily depend on the prior mean and variance: What is our best guess before looking at the data? How confident are we? In the absence of a true prior, intuition suggests we can build an effective prior from the mean and variance[26]

[25] This takes the form $\tilde{F} = E(F|r)$, where F is the factor covariance matrix, and the asset returns r are governed by a factor model $r = Xf + u$. The factor returns f are not directly observable, but instead must be estimated from the asset returns, typically as $\hat{f} = (X'X)^{-1}X'r$. However, the sample covariance of $\hat{f}$ is not the best estimate of the true covariance matrix, and is biased by the noise in $\hat{f}$. The Bayesian estimator $\tilde{F} = E(F|r)$ is unbiased and significantly less noisy.

[26] This is almost right, but with one wrinkle. The observed dispersion of observations is broadened from the distribution of true values by the sampling error in the observations. Roughly, the observed variance is the true variance plus the sampling error.

of observations of related quantities. Bayesian statistics can be used to give mathematical precision[27] to these intuitive ideas.

The MSCI Private Real Estate Factor Model uses induced priors to reduce noise in estimates of smoothing and risk parameters. For each parameter estimated in the model, peer groups are defined over related parameters. For example, the smoothing parameter of each factor is assigned a peer group of similar factors. For many markets, the peer group is assigned based on the results of a survey of valuation transparency in each market; for example, Thailand, Ireland, Portugal, Taiwan and the Czech Republic have had the lowest scores for valuation transparency, and the factors in these models define a peer group for smoothing parameters.

In the extreme that no data is available for a segment of the market, the induced prior can be used to build risk forecasts based on similar segments of other markets. For example, Malaysian Hotels may have the same relationship to other segments of the Malaysian market as Hotels do in other Asian markets. The result may be more accurate in gauging diversification and correlations of a Malaysian real estate portfolio than if a more typical proxy approach were used.

Simulation studies

Simulations are a useful tool for evaluating the effectiveness of risk methodology. Private asset data is too scarce and too smooth for standard back-testing. It is often difficult to build even a single risk forecast, let alone a series long enough to test against many independent return observations. Simulations also make it possible to lift back the curtain, and compare various risk estimates with the true values underlying the simulations.

The table below shows some results of a broad simulation study of desmoothing techniques, and underlying smoothing processes. In all cases, 40 quarters of public and true private asset returns are simulated[28] with a correlation of 70%, followed by a variety of smoothing processes:

- AR(1) Constant Smoothing: The most benign form of smoothing
- AR(1) Seasonal Smoothing: Four different smoothing parameters are applied
- AR(1) Random Smoothing: A random smoothing parameter is used each period
- AR(4) Constant Smoothing: A multi-lag generalization of standard smoothing
- MA(4) Constant Smoothing: A multi-lag generalization of standard smoothing

See Footnote 15 for a definition of the AR(4) and MA(4) processes.

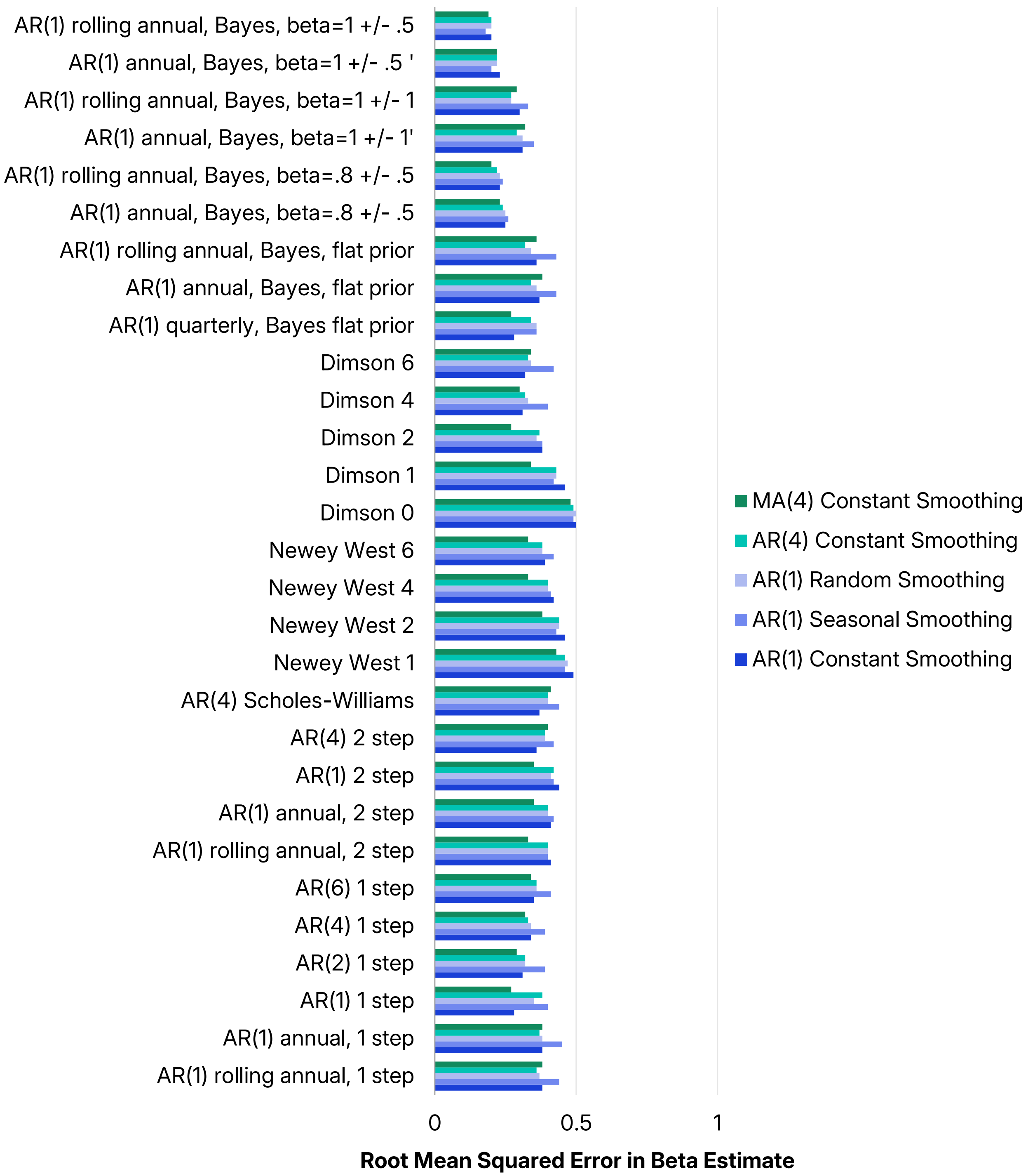
[27] For noisy observations $\hat{x}_i$ of quantities x_i in a peer group, we can take the conditional expected value of a particular value i relative to observations over the whole peer group, $E(x_i|\hat{\boldsymbol{x}})$, not just $E(x_i|\hat{x}_i)$. If the noise is independent across observations, then the conditional probability $p(x_i|\hat{\boldsymbol{x}})$ can be written as $p(\hat{x}_i|x_i)\tilde{p}(x_i;\hat{x}_{j\neq i})/p(\hat{x}_i)$. The *induced prior* $\tilde{p}(x_i;\hat{x}_{j\neq i})$ acts as a prior $p(x_i)$. Roughly, the induced prior for observation i takes the shape of the empirical distribution of the other observations $\hat{x}_{j\neq i}$.

[28] The true private returns are simulated as public return + pure private return, with a beta chosen arbitrarily to be 1. The relative degree of noise depends on the public-private correlation, chosen to be 70% for this simulation, but not on the value of beta, or the volatility of the time series.

The private-public beta is estimated from the simulated series using a range of estimators:

- One-step versus two-step estimators: As discussed in *Appendix A: Methodology details* two-step estimators first apply desmoothing to the private time series, then estimate beta from the desmoothed returns
- Bayesian: The class of estimators used in the MSCI Private Real Estate Factor Model, described in *Appendix A: Methodology details,* generalizing the AR(1) (Rolling) Annual one-step estimators. A range of priors for beta is studied
- AR(n) One-step: Applies n lags of desmoothing, and two lags of serial correlation with the public returns
- Annual estimators: Use only annual returns
- Rolling Annual Estimators: Average beta estimated from four versions of annual returns, starting in Q1, Q2, and so forth
- Dimson: A type of one-step estimator (see Dimson (1979) and Dimson (1985)).
- Scholes-Williams: A type of two-step estimator (see Scholes (1977)).
- Newey-West: Constructs beta from estimates of a covariance matrix accounting for serial correlation (see Newey (1987)).

Desmoothing and risk estimation simulation



A simulation study tests a variety of desmoothing and risk estimation methods over a range of underlying smoothing processes. The root mean squared error measures the average deviation of an estimate of beta from the true value of 1: lower values are better. PEQ2 uses Bayesian estimators with priors of moderate confidence (like the ±.5 here), which do significantly better than other approaches.

The results of the simulation shown in the above table reveal a wide range of forecast accuracy, and point to a number of conclusions for estimating risk of private assets.

The **robustness** of estimators varies significantly. For example, the AR(1) one-step estimator performs well if the smoothing follows the process it assumes, but is much less accurate if other processes are at work.

The possible **seasonality** of appraisals poses a challenge to many estimators. Unfortunately, the seasonal smoothing process may come closest to the actual form of smoothing in the markets.

The performance of **single step** estimators is significantly better than the two-step estimators. As discussed in *Appendix A: Methodology details,* the single-step estimators take advantage of the public returns to better distinguish smoothed returns from coincidental runs of similar returns.

The Newey-West estimators perform poorly in this regime of very high autocorrelation. In order to capture enough "echoes" of the large inherent autocorrelation, the Newey-West estimator must use many lags, introducing noise.

The benefits of quarterly data are small compared with **annual data**. For all but the simplest smoothing process, the benefits of more data points are offset by the need to estimate more parameters to capture the smoothing at the quarterly horizon, and the lack of independence between smoothed quarterly returns.

Higher **complexity** does not benefit the estimation. Even for returns following the AR(4) process for which it is designed, the AR(4) one-step estimator is less accurate than the AR(2) one-step estimator. Although the AR(4) estimator is "correct" in this context, the additional parameters introduce noise.

Most striking of all, however, is the significant gains in accuracy that come from the use of the **Bayesian estimators**. Even in the absence of any priors, the Bayesian approach tends to do better than standard approaches. Once priors are incorporated, the gains become striking.

It is notable that even an **incorrect prior does better** than a correct prior imposed without sufficient conviction. The prior of .8 ± .5 for beta is smaller than the true beta of 1, but the tighter confidence intervals result in more accurate forecasts than the accurate but wide prior of 1 ± 1. It is best to have an accurate prior, but it can be even more important to avoid being too conservative with the prior.

We cannot know the true processes at work in the markets, nor the accuracy of our priors, but the Bayesian estimators used in our model are seen to be far more accurate than other approaches, over a wide range of possible scenarios.

The results shown in the table above are a sample from a broader simulation study, which looked at a broad range of parameter values, and studied more complicated effects and estimators, such as the thin-factor corrections discussed in *Appendix A: Methodology details.*

Another sample from this study is shown in the table below, which shows the average values of risk parameters produced with various estimators. The naïve estimates based on raw returns are far from the true values, giving an appearance of lower risk across all risk measures. Standard desmoothing gives significantly higher estimates of risk and correlation than the naïve estimates, and relatively unbiased estimates of beta. Overall, standard desmoothing is seen to provide significantly more accurate estimates of risk than the raw returns.

However, the estimates of the residual risk are biased upward, a bias which can be as large as a factor of five for some choices of parameters. The bias gives the impression that private real estate has lower correlation, and provides greater diversification, than the true parameters of the simulation.

Correcting this bias with the Bayesian estimator leads to a further increase in the correlation estimates. The bias depends on the details of the parameters chosen, but in this fairly typical example the average of 81% is much closer to the true 80% than either the raw 57%, or standard 73%.

The economic interpretation of this is significant: **Real estate is an asset class**. The return of public and private real estate may be influenced by a variety of important factors, such as differing liquidity premia, as discussed in the *Methodology overview* section. However, the long-run returns of these assets are seen to have far more commonality than the standard approaches to smoothing have shown.

Average risk parameters from simulation study

	Total Risk	Beta	Correlation	Residual Risk
True	12.5%	1.00	80.0%	7.5%
Raw Returns	5.3%	0.30	57.5%	4.3%
Standard Desmoothing	7.1%	0.51	72.8%	4.8%
Bayesian Desmoothing	12.6%	1.01	81.2%	7.3%

Average values of risk parameters in a simulation study of different risk estimators. The true values of these parameters are set in the simulation with the values in the top row. In this simulation, a relatively mild set of parameters is chosen: The smoothing process is a simple AR(1) with constant coefficient, and 30 years of quarterly returns are used.

Public proxies

The public proxy plays an important role in linking private real estate to the public markets. As discussed in the *Methodology overview* section, no public proxy can fully capture the behavior of private real estate, but public proxies do provide a timely, market-based view of real estate that complements the pure private factors in the model.

Listed real estate funds typically do not specialize to the level of granularity of the property-type-by-location factors of the MSCI Private Real Estate Factor Model, but often do specialize within property types. This makes it possible to construct property-type public proxies in many countries, which are further refined with private asset data, as discussed in the *Methodology overview* section.

In markets with fewer listed real estate assets, an important role is played by the Bayesian thin-factor corrections of *Appendix A: Methodology details.* An index of broad listed real estate[29] in each country acts as a prior, from which the property-type specific factors deviate to an extent determined by the Bayesian statistics. Markets with fewer listed real estate assets allow less refinement among property types, but they need not have more noise.

In some markets[30] almost no listed real estate is available, and a broader proxy is needed. For these markets, a proxy is built from listed real estate in nearby, similar markets as:

$$Country\ Real\ Estate = Regional\ Real\ Estate - Regional\ Market + Country\ Market$$

Similar to regional factor models, this models a country's real estate as country + pure real estate, the latter estimated from the region.

To serve as a closer proxy for private real estate, the proxies are constructed from *delevered* listed real estate returns, where the leverage is applied at the level of individual securities:

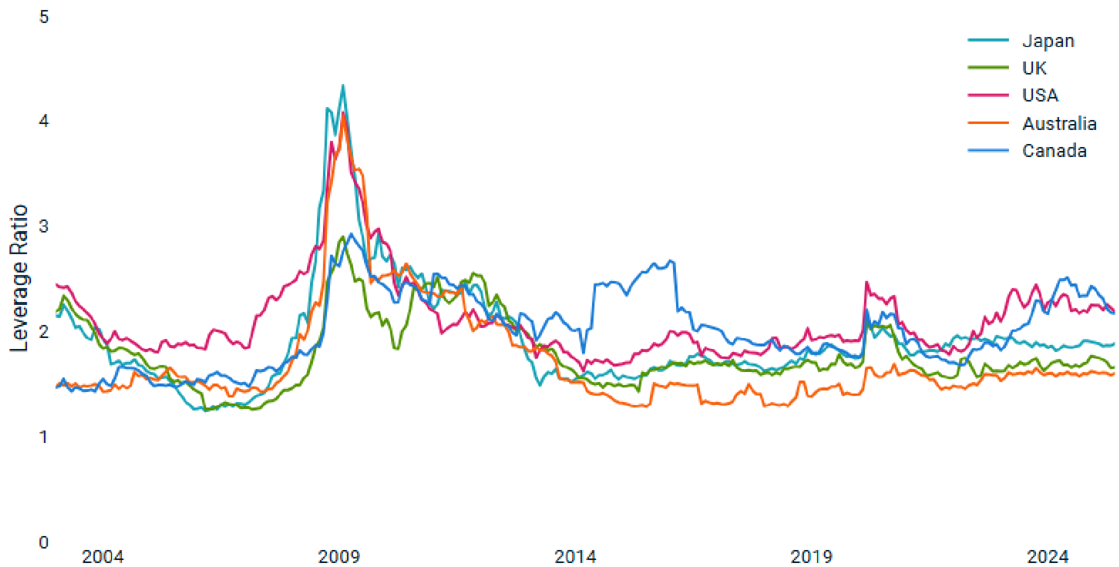
$$Asset\ Return\ = \frac{Equity}{Debt + Equity}\ Equity\ Return$$

If leverage were constant, risk forecasts could be made using either a raw or delevered listed real estate proxy. The difference would be absorbed in the private-public beta as $\beta \to \beta \times leverage\ ratio$. However, as seen in the chart below, leverage ratios can fluctuate significantly over time (as well as over assets). If debt levels are approximately constant, a drop in asset values — such as occurred during the 2008 global financial crisis — causes a far larger relative change in equity, and a spike in the leverage ratio. As a result, there is no single leverage ratio that can properly convert the beta to a like-to-like delevered real estate proxy.

[29] In many countries, the broader real estate sector is used for the prior, including non-REITs, to achieve a wider sample size. In Korea, Construction assets are also included. In markets where a wide sample of assets is available, REITs tend to be highly correlated with both broader real estate and construction.

[30] Region-based proxies are used for the Czech Republic, Hungary, Ireland, Norway, Poland and Portugal.

Listed real estate leverage



The leverage ratios of listed real estate vary significantly over time, with a significant spike driven by declining asset values during the great financial crisis.

For distressed assets, a subtlety arises in the relationship between the (observable) equity value and the (unobservable) value of the underlying assets. In addition to the standard Equity = Assets – Debt, the limited liability of equity introduces an additional component to the equity value, which the Merton Model (see Merton (1974)) attributes to the option value of the limited liability. The option value softens the relationship[31] between equity and asset values, so that deleveraging by the standard leverage ratio results in artificially low estimates of the asset returns.

For example, deleveraging by (Debt+Equity)/Equity would result in a steadily declining volatility in Spain over the period from 2007 through 2013, a rather unintuitive behavior for a country in the throes of a real estate driven financial crisis. The precise equity-asset relationship of the Merton model depends on the details of the debt and assets, but an effective leverage ratio capped at 3 approximates the behavior for reasonable parameter values.

In addition to correcting the distortions from time-dependent leverage, delevered public proxies also facilitate the definition of priors for the private-public beta. In the absence of any data, we may not have

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[31] In the Merton Model, the asset returns are related to the equity returns as

$$Asset\ Return = \frac{Equity}{\Delta_{Call} \cdot Assets}\ Equity\ Return.$$

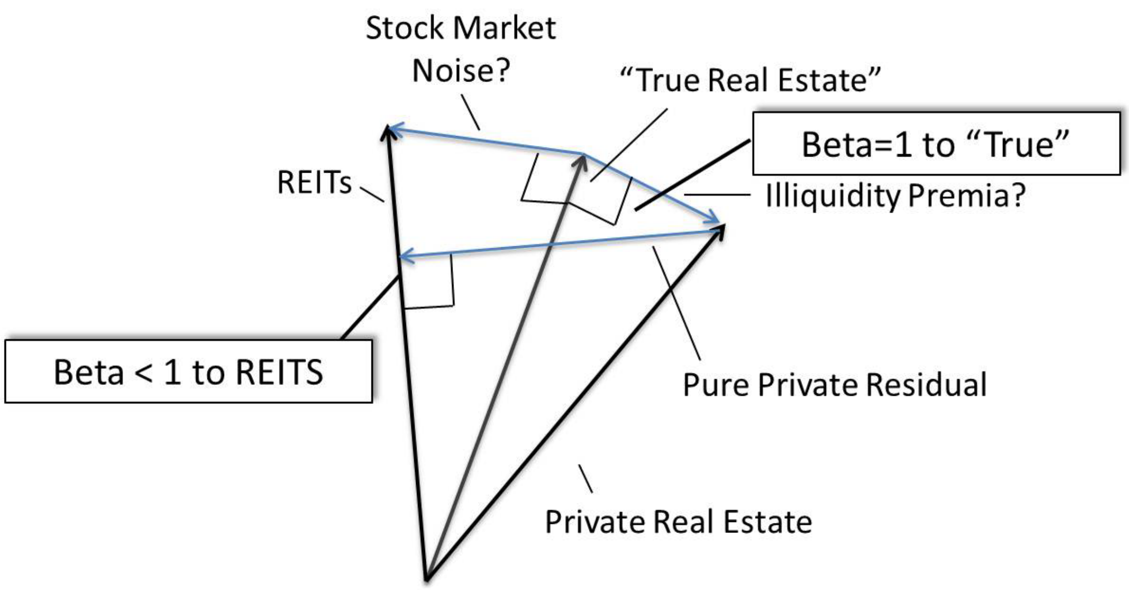
Since the Merton model's call option delta $\Delta_{Call} < 1$ and $Assets < Debt + Equity$, deleveraging by the standard leverage ratio overstates the proportionality coefficient, and results in artificially low estimates of the asset returns. In the extreme that the property is under water, $Debt + Equity < 0$, and the standard leverage ratio breaks down, but the option value of the Merton model results in positive equity value and equity-asset proportionality coefficient.

a strong prior for the beta between delevered private real estate and levered listed real estate, but we could expect a delevered-to-delevered beta close to one.

In the presence of the additional layers of return for listed real estate, discussed in the *Methodology overview* section, the prior expectation for beta should actually be somewhat less than 1. The graphic below depicts the case in which both listed and unlisted real estate differ from "true" real estate, as in Ang (2013).[32] Larger stock market "noise" tends to decrease the private-public beta, with an expected beta of 1 only in the absence of noise in the public proxy.

An appropriate prior can be calibrated from the specific risk and the number of assets in the public proxy, and the broad distribution of observed betas among private real estate factors. An initial beta prior of .85±.3 is applied for most factors, with values reduced as low as .6 for a handful of particularly thin public proxies. The value of .85 is consistent with "noise" representing a little more than 15% of the total variance of the public proxy.

Beta is expected to be less than 1



In the presence of any additional layers of return to listed real estate, depicted as stock market noise, the expected beta of private real estate to delevered public real estate is somewhat less than 1.

[32] We use a similar construct to the idea of "true" real estate as Ang (2013). True real estate can potentially differ from both private real estate — perhaps due to liquidity effects — and also may differ from listed real estate — due either to short-term inefficiency in the stock markets, or simply to estimation error in the public proxies. However, our Bayesian methodology differs from that of Ang. In particular, we do not apply desmoothing at the quarterly horizon, to avoid distortions caused by the seasonality of appraisals.

Transaction Linked Indexes

As discussed in the *Methodology overview* section, real estate transactions can provide a third source of insight into real estate, providing the true values paid for private real estate.

MSCI has addressed the problem of the long intervals between transactions for individual properties with the construction of **Transaction Linked Indexes** (TLI) (see IPD Index Guide (2012)). These indexes are constructed by comparing the prior appraisals to the actual transaction prices of properties that are sold, providing a more timely and less smoothed view of property values. The differences between the transaction prices and the previous appraisals are used to update the broader appraisal-based indexes to reflect current market conditions before they are reflected in the smooth appraisals. The transaction-linked indexes have the advantage of providing a more timely, market-based valuation.

Since only a fraction of properties transact in any observation period, the transaction linked indexes tend to have a smaller sample size and less granularity than the corresponding valuation-based indexes (VBI). Further, the properties that transact are not a random sample of the overall market, but may exhibit a range of selection biases under different markets. A "zig-zag" pattern of returns sometimes results from the influence of individual transactions moving the indexes, which then mean-revert in subsequent periods. The TLI are therefore used to complement, rather than replace, the valuation-based indexes.

The MSCI Private Real Estate Factor Model uses TLI timeseries in the markets listed in the table below to provide additional estimates of risk, which are then blended with the VBI-based estimates using the Bayesian techniques of *Appendix A: Methodology Details*.

Transaction Linked Indexes are used for the following markets to complement the information in the Valuation Based Indexes

Country	# Indexes	Inception
Germany	1	2002/3
Denmark	5	2002/3
France	5	2002/3
Ireland	1	2002/3
Netherland	5	2002/3
Norway	5	2002/3
Sweden	5	2002/3
Switzerland	5	2003/3
U.K.	4	2002/6

Appendix B: Data

The private real estate data used to estimate the MSCI Private Real Estate Factor Model plays a central role in calibrating the differences in risk among the 400+ segments of the market captured by the model. Our data collection and classifications are tailored to each market. While our model provides consistency with the common property-type segmentation across all markets, the definitions of these property-types, and their regional breakdowns, reflect what is important to each market on a country-by-country basis.

For the United States, MSCI data is supplemented with data from the National Council of Real Estate Investment Fiduciaries (NCREIF) in two areas: For the deep history of core real estate, and for Farmland and Timberland. For the period starting in 1999 when data is available in both MSCI and NCREIF, the statistical properties are very similar. The MSCI data has the advantages of additional granularity, and the inclusion of the Other property type. For segments of the market that NCREIF does cover, however, the choice of input data source is immaterial.

Appendix C: Model coverage

MSCI Private Real Estate Factor Model covers private real estate from 31 countries, and farmland and timberland in the US and UK

Country	# factors	Country	# factors
Australia	13	Netherlands	19
Austria	9	New Zealand	11
Belgium	10	Norway	14
Canada	16	Poland	7
China	7	Portugal	13
Czech Republic	7	Singapore	7
Denmark	16	South Africa	9
France	15	South Korea	14
Germany	15	Spain	11
Hong Kong	7	Sweden	15
Hungary	7	Switzerland	18
Indonesia	7	Taiwan	7
Ireland	15	Thailand	7
Italy	11	United Kingdom	33
Japan	18	United States	66
Malaysia	7		

The factors of the private real estate models

Australia
Hotel
Industrial Melbourne
Industrial Rest of Australia
Industrial Sydney
Office Brisbane
Office Canberra
Office Melbourne
Office Rest of Australia
Office Sydney
Other
Residential
Retail
Income Return

Austria
Hotel
Industrial
Office Vienna Bezirk 1
Office Vienna Bezirk 2-9
Office Vienna Other
Other
Residential
Retail
Income Return

Belgium
Hotel
Industrial
Office Brussels CBD
Office Brussels Decentralized
Office Outer Brussels
Office Rest of Belgium
Other
Residential
Retail
Income Return

Canada
Hotel
Industrial Ontario
Industrial Rest of Canada
Office Alberta
Office British Columbia
Office Ontario
Office Quebec
Office Rest of Canada
Other
Residential
Retail Alberta
Retail British Columbia
Retail Ontario
Retail Quebec
Retail Rest of Canada
Income Return

China
Hotel
Industrial
Office
Other
Residential
Retail
Income Return

Czech Republic
Hotel
Industrial
Office
Other
Residential
Retail
Income Return

Denmark
Hotel
Industrial
Office Copenhagen Broer and Frederiksberg
Office Copenhagen CBD
Office Copenhagen Harbour Area
Office Copenhagen North
Office Copenhagen Other
Office Copenhagen South and West
Office Odense Aalborg Aarhus Triangle Area
Office Rest of Denmark
Other
Residential Copenhagen
Residential Odense Aalborg Aarhus Trangle Area
Residential Rest of Denmark
Retail
Income Return

France
Hotel
Industrial
Office Other Region
Office Paris CBD
Office Paris Other Area
Office Rest of Ile de France
Office Rest of Petite Couronne
Office Western Crescent La Defense
Other
Residential Other Region
Residential Paris West Centre Neuilly
Residential Rest of Ile de France
Residential Rest of Paris
Retail
Income Return

Germany
Hotel
Industrial
Office Berlin
Office Cologne
Office Dusseldorf
Office Frankfurt
Office Hamburg
Office Munich
Office Other City
Office Stuttgart
Other
Residential
Retail Major City
Retail Other City
Income Return

Hong Kong
Hotel
Industrial
Office
Other
Residential
Retail
Income Return

Hungary
Hotel
Industrial
Office
Other
Residential
Retail
Income Return

Indonesia
Hotel
Industrial
Office
Other
Residential
Retail
Income Return

Ireland
Hotel
Industrial North Dublin
Industrial South
Industrial Southeast Dublin
Office Central Dublin
Office Provincial
Office Rest of Dublin
Other
Residential
Retail Grafton Street
Retail Henry Mary Street
Retail Other City Center
Retail Provincial
Retail Suburban Dublin
Income Return

Italy
Hotel
Industrial
Office Center South
Office Milan
Office North East
Office North West
Office Rome
Other
Residential
Retail
Income Return

Japan
Hotel
Industrial
Office Fukuoka-shi
Office Kawasaki-shi Yokohama-shi
Office Nagoya-shi
Office Osaka-shi
Office Rest of Japan
Office Rest of Tokyo
Office Tokyo 5 wards
Other
Residential Osaka
Residential Rest of Japan
Residential Rest of Tokyo
Residential Tokyo 5 wards
Retail Osaka
Retail Rest of Japan
Retail Tokyo
Income Return

Korea
Hotel
Industrial Rest of Korea
Industrial Seoul
Office Rest of Korea
Office Rest of Seoul
Office Seoul CBD
Office Seoul KBD
Office Seoul YBD
Other
Residential Rest of Korea
Residential Seoul
Retail Rest of Korea
Retail Seoul
Income Return

Malaysia
Hotel
Industrial
Office
Other
Residential
Retail
Income Return

Netherlands
Hotel
Industrial East Netherland
Industrial North Netherland
Industrial Randstad
Industrial South Netherland
Office East Netherland
Office North Netherland
Office Randstad
Office South Netherland
Other
Residential East Netherland
Residential North Netherland
Residential Randstad
Residential South Netherland
Retail East Netherland
Retail North Netherland
Retail Randstad
Retail South Netherland
Income Return

New Zealand
Hotel
Industrial Auckland
Industrial Wellington
Office Auckland
Office Wellington
Other
Residential Auckland
Residential Wellington
Retail Auckland
Retail Wellington
Income Return

Norway
Hotel
Industrial
Office Bergen
Office Oslo CBD
Office Oslo Central Area
Office Oslo East South
Office Oslo West North
Office Rest of Norway
Office Stavanger
Office Trondheim
Other
Residential
Retail
Income Return

Poland
Hotel
Industrial
Office
Other
Residential
Retail
Income Return

Portugal
Hotel
Industrial Lisbon
Industrial Rest of Portugal
Office Lisbon CBD
Office Lisbon New Office Areas
Office Lisbon Out of the Town
Office Lisbon Secondary
Office Portugal
Office Rest of Portugal
Other
Residential
Retail
Income Return

Singapore
Hotel
Industrial
Office
Other
Residential
Retail
Income Return

South Africa
Hotel
Industrial
Office City Decentralized
Office Inner City
Office Provincial
Other
Residential
Retail
Income Return

Spain
Hotel
Industrial
Office Barcelona Other
Office Barcelona Prime CBD
Office Madrid CBD Other Central
Office Madrid Other
Office Rest of Spain
Other
Residential
Retail
Income Return

Sweden	Thailand
Hotel	Hotel
Industrial	Industrial
Office Goteborg	Office
Office Malmo	Other
Office Rest of Greater Stockholm	Residential
Office Rest of Sweden	Retail
Office Stockholm CBD	Income Return
Office Stockholm Central Area	**United Kingdom**
Other	Hotel
Residential Goteborg and Malmo	Industrial London
Residential Rest of Greater Stockholm	Industrial Rest of UK
Residential Rest of Sweden	Industrial South East
Residential Stockholm Central Area	Office City
Retail	Office Rest of London
Income Return	Office Rest of UK
Switzerland	Office South East
Hotel	Office West End Midtown
Industrial	Other
Office Basle	Residential
Office Berne	Retail London
Office Geneva	Retail Rest of UK
Office Lausanne	Retail South East
Office Rest Switzerland	Income Return
Office Zurich	Logistics
Other	Self Storage
Residential Basle	Other Industrial
Residential Berne	CBD Office
Residential Geneva	Suburban Office
Residential Lausanne	Other Office
Residential Rest Switzerland	Social Housing Subsidized Housing
Residential Zurich	Suburban Residential
Retail Major City	Urban Residential
Retail Other City	Other Residential
Income Return	Mall Regional Super Regional Center
Taiwan	Neighborhood Community Convenience Center
Hotel	Open-Air Shopping Center Retail Park
Industrial	Retail Warehouse Big Box Retail
Office	Other Retail
Other	
Residential	**UK Agriculture**
Retail	Forestry
Income Return	Rural

United States
Hotel
Industrial East
Industrial Midwest
Industrial South
Industrial West
Office East
Office Midwest
Office South
Office West
Other
Residential East
Residential Midwest
Residential South
Residential West
Retail East
Retail Midwest
Retail South
Retail West
Income Return
Logistics
Self Storage
Other Industrial
CBD Office
Suburban Office
Other Office
Social Housing Subsidized Housing
Suburban Residential
Urban Residential
Other Residential
Mall Regional Super Regional Center
Neighborhood Community Convenience
Open-Air Shopping Center Retail Park
Retail Warehouse Big Box Retail
Other Retail

United States
Atlanta
Boston
Chicago
Dallas
Denver
Houston
Los Angeles
New York
SF Bay Area
San Diego
Seattle
South Florida
Washington DC
Rest of Midwest
Rest of Northeast
Rest of South
Rest of West

US Agriculture
Annual Crop Corn Belt
Annual Crop Delta States
Annual Crop Lake States
Annual Crop Mountain
Annual Crop Pacific Northwest
Annual Crop Pacific West
Annual Crop South Plains
Annual Crop Southeast
Forestry Lake States
Forestry Northeast
Forestry Northwest
Forestry South
Permanent Crop Lake States
Permanent Crop Pacific Northwest
Permanent Crop Pacific West

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