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Market risk of real estate:
Using indirect data to understand direct risks

The Journal of Financial Perspectives

EY Global Financial Services Institute

November 2013 | Volume 1 – Issue 3

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Executive summaries

Market risk of real estate: Using indirect data to understand direct risks

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Even if the market capitalization of direct real estate is comparable to that of equities and fixed income, the data on direct real estate is very poor. It is, therefore, difficult to estimate the market risk of this important asset class. Moreover, risk systems from most vendors cover equities and fixed income, but do not cover direct real estate. This paper proposes a simple methodology that uses widely available data on indirect real estate to estimate the market risk of direct real estate. In particular, we use data on Real Estate Investment Trusts (REITs) returns, determine their factor exposures to other asset classes and deleverage these exposures according to REITs' balance sheets. The paper shows that direct real estate can be considered as a portfolio of equities, fixed income and credit, combined with idiosyncratic risk. The authors find that the existing direct indices understate the risk of the real estate market. In addition, with the proposed methodology, the correlations to other asset classes become materially different and higher.

Market risk of real estate: Using indirect data to understand direct risks

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Abstract

Even if the market capitalization of direct real estate is comparable to that of equities and fixed income, the data on direct real estate is very poor. It is, therefore, difficult to estimate the market risk of this important asset class. Moreover, risk systems from most vendors cover equities and fixed income, but do not cover direct real estate. We propose a simple methodology that uses widely available data on indirect real estate to estimate the market risk of direct real estate. In particular, we use data on Real Estate Investment Trusts (REITs) returns, determine their factor exposures to other asset classes and deleverage these exposures according to REITs' balance sheets. We show that direct real estate can be considered as a portfolio of equities, fixed income and credit combined with idiosyncratic risk. We find that the existing direct indices understate the risk of the real estate market. In addition, with our methodology, the correlations to other asset classes become materially different and higher.

Introduction

Direct real estate is the largest asset class without readily available prices. It is difficult to observe direct real estate data because transactions have low frequency and are often private. It is also difficult to interpret the few data that can be found because properties are heterogeneous and often difficult to compare. There exist many methodologies that try to solve these problems, such as the appraisal-based indices, the transaction-based indices and the hedonic approach. Nevertheless, all these methodologies present important challenges and are difficult to use for practical applications. These data issues make the market risk of real estate poorly understood. This paper proposes a simple model that allows using widely available data on indirect real estate to achieve a better understanding of the direct real estate market risk.

We propose to use widely available data on real estate investment trusts (REITs) to acquire a more accurate knowledge of real estate market risk. REITs are closed-end funds that invest in direct real estate and are financed with equity and debt. REITs are openly traded in the market and provide abundant and frequent data. They are more transparent than direct real estate indices, and also relatively more price-efficient. Indeed, REITs are required to prepare standardized public financial statements and accurate performance measurements, which make it easier to re-price assets on a timely fashion.

There is an abundant literature supporting a close link between REITs and direct real estate. Our paper proposes a simple model to apply these widely accepted findings to the practical problem of real estate risk management and portfolio allocation. Building on the work documented in Schlumpf and Tessera (2010), our model is based on the simple observation that a REIT is a real estate company that can be described as a portfolio of direct property investments financed by mortgages or bonds. With this observation, we are able to build a bridge between direct and indirect real estate that we use to better understand the market risk of direct real estate.

Using REIT balance sheet data, we are able to translate indirect real estate risk factor decompositions into direct real estate risk factor decompositions. This approach enables us to represent direct real estate as a portfolio of equities, fixed income and credit combined with an idiosyncratic risk. This is useful for practical risk and asset management decisions given that risk systems from most market vendors cover equities and fixed income as asset classes, but not direct real estate. Our methodology offers a simple, transparent and accurate description of the real estate asset class and of its market risk.

We find that the estimations of real estate volatility that can be derived from the existing methodologies considerably understate the risk of the real estate asset class. Indeed, taking into account the case of the U.K., which has good availability of both direct and indirect real estate indices, we are able to compare the volatility resulting from our model to that of direct real estate indices, both appraisal-based and transaction-based. We find that the volatility that results from our model is almost three times bigger than that of direct real estate appraisal-based indices, and two times bigger than transaction-based ones.

Moreover, we find that the correlations between real estate and risky assets resulting from our methodology are substantially higher than those resulting from the traditional approaches. This has important implications for risk management and asset allocation. Our results are particularly important in the light of the role that real estate played in the recent financial crisis. Indeed, in our model the price movements that took place in the recent crisis correspond to less than a two standard error move.

Recent literature

The majority of benchmarks for direct investments in real estate are appraisal-based. They are usually smoothed and tend to lag the returns in the property markets. Moreover, appraisal-based indices understate the volatility of real estate investments and their correlation to other asset classes, making them inadequate to describe market risk and to guide portfolio diversification. Moreover, the history of most direct indices is quite short and the data frequency is low.

A more accurate way for constructing direct real estate indices would be to use the hedonic method. Nevertheless, this methodology requires remarkable datasets containing information such as physical characteristics, neighborhood, area, distance to the city center, etc. Since this kind of data is often not available, the hedonic method is difficult to apply in practice.

A vast amount of research is devoted to providing solutions to the problems presented by direct appraisal-based indices. In particular, several authors have attempted to provide techniques to unsmooth these indices, which tend to be particularly autocorrelated because appraisers usually keep their estimations fairly constant over time. Indeed, even if there exists an established standardized appraisal methodologies, appraisal-based indices tend to lag the market and understate volatility because appraisers usually smooth their valuations over time. Suryanarayanan and Stefek (2010) argue that the lag between appraisal and market values is between three months, when transaction volumes are high, and one year, when they are low.

General unsmoothing techniques apply a statistical filter to the appraisal-based returns to remove the autocorrelation in the series. Nevertheless, these procedures present several problems. In particular, Bond et al. (2006) argue that autocorrelation filters tend to overstate the smoothing that takes place at the individual property level. They argue that while idiosyncratic shocks are cancelled out when individual property level appraisals are aggregated, common shocks are not, and they tend to be highly persistent. This persistency is due to the illiquidity of the real estate market that impedes arbitrageurs to exploit shocks. Moreover, common factors may be related to macroeconomic fundamentals that tend to evolve slowly over time. The bias of the unsmoothing techniques arises because autocorrelation filters are applied to the aggregate indices and not to the individual ones. As a result, these procedures overstate the smoothing and may result in misleading information.

Transaction-based indices are often proposed as an alternative to appraisal-based indices. Nevertheless, transaction based indices may contain a lot of noise, as the baseline information often presents outliers. Moreover, transactions have low frequency, are often private, and it is unclear if the observed ones can be considered representative of the market.

Some authors have developed techniques to address the fact that real estate property transactions do not occur very often. For example, Sheharyar and Geltner (2012) propose a two-stage frequency conversion methodology to increase the frequency of direct real estate data. Nevertheless, this approach tends to lag behind the estimation. Other econometric models aimed at solving the problems posed by the transaction approach have been proposed by Fisher et al. (2007) in the MIT Centre for Real Estate for the case of the U.S., and Devaney and Martinez Diaz (2010) for the case of the U.K..

A growing literature has departed from the transaction-based approach to consider how REIT data can serve as a proxy for the direct real estate market. For example, Suryanarayanan (2011) describes the methodology implemented by MSCI Barra, which by unsmoothing private index returns finds a close relationship between direct and indirect real estate investments. The correlations (between REITs and direct real estate) in the long run model for the U.S. are between 40% and 60%, while for the U.K. they are between 50% and 65%. Similarly, Suryanarayanan and Stefek (2010) find a strong link between annual returns to public and private real estate in the U.K. and U.S. markets. These authors correct for appraisal smoothing and take into account the lead-lag relationship between the two asset returns. They find that the relationship between direct and indirect real estate is stronger as the time horizon increases.

Sebastian and Schätz (2009) include economic fundamentals in the analysis of the relationship between direct and indirect real estate indices. Including macroeconomic variables is very important because it helps to control the effects that these variables may have on the comovement between REITs and direct real estate. These authors focus on the overall real estate market and do not consider the specificities of different sectors. Pavlov and Wachter (2011), on the other hand, take into account economic fundamentals and different real estate sectors, but not the influence of lead-lag relations or the long-run behavior of the assets.

Hösli and Oikarinen (2012) propose the most rigorous and complete study to our knowledge. Using quarterly data for U.S., U.K. and Australia, and a Vector Error Correction Model (VECM), these authors derive impulse response functions of the asset returns, which allow estimating the reaction patterns that REITs and direct real estate returns have to shocks in economic fundamentals and in the asset returns themselves. The variance decompositions proposed show that, in the long term, the forecast error variance of direct real estate returns is explained mostly by shocks to REITs. This implies that securitized and direct real estate returns are driven by a common "real estate factor," given that the fundamental asset is essentially the same in both markets. Consequently, in the long run, direct and indirect real estate are closely related.

Moreover, Hösli and Oikarinen (2012) find that in the long run shocks in the stock market do not have an influence in the variance of REITs' shocks. REITs, therefore, provide the same diversification benefits that direct real estate does, making direct and indirect real estate good substitutes in the long term. Furthermore, the authors find that even if REITs shocks help in predicting the variance of direct real estate shocks in the long run, the opposite does not hold.

This suggests that real estate shocks take place first in the REIT market, and only then the direct market adjusts. Consequently, using REIT data may be more useful for predicting crisis and recovery periods. This is similar to the findings of Cotter and Roll (2011), who argue that REITs can provide useful information for predicting collapses in the real estate market, such as the one that was closely associated with the recent financial crisis.

We rely on this evidence to use REIT data for performing an accurate risk factor analysis of the real estate asset class. Building on the model proposed by Schlumpf and Tessera (2010), we focus in this paper mostly on the risk management implications of using REIT data to improve our understanding of the real estate asset class. We do so by estimating the risk factor exposure of REIT returns and deleveraging it to obtain the risk factor exposure of direct real estate.

A similar approach to ours is developed by Horrigan et al. (2009), who construct property market returns indices by using data on REITs' returns, bonds and property holdings. According to these authors, the beneficial characteristics of REITs allow us to detect the price movements of the underlying property markets on a daily basis without having to observe property transactions, which occur with low frequency. To achieve this, they combine information on REIT asset holdings and stock returns using the weighted average cost of capital (WACC) accounting identity. The resulting so-called "pure play" indices can be used to make targeted investments in the commercial real estate market, while keeping the advantages of REITs, such as liquidity, transparency and pricing efficiency.

Our approach is different from that of Horrigan et al. (2009) because we focus on the practical applications of using the WACC identity and REIT data for achieving a better risk analysis of the real estate asset class, and therefore producing better risk estimates. Indeed, while Horrigan et al. (2009) want to build new and more accurate data, as well as to propose the grounds for new investment instruments, our approach is aimed at deriving real estate risk factor exposures in a more accurate way, so as to provide a better understanding of the real estate risk that is useful in empirical applications.

Some studies have focused on the insights regarding the risk of real estate that can be derived by comparing direct and indirect real estate risks. In particular, Cotter and Roll (2011) propose an exhaustive comparison of the returns, risk, and distributional characteristics of REITs and residential real estate indexes, using S&P Case Shiller monthly data. They find that smoothed residential real estate series tend to have lower volatilities than REITs. According to these authors, direct real estate volatility is around 1/5 of REITs volatility.

Nevertheless, Cotter and Roll (2011) point to the problem that it is not clear whether the smoothed residential real estate series that they used really reflected the direct real estate prices. This problem is taken into account by Devaney and Martinez Diaz (2010), who argue that transaction-based indices help to find a more precise estimation of real estate market risk, as compared to appraisal-based indices. We propose to go one step further and take into account the widely available data on REITs to produce simpler, and more accurate and transparent estimations of the direct real estate market risk.

Our approach is of particular interest given that, after the protagonist role that real estate had in the recent financial crisis, a growing attention has been given to extreme risks in real estate markets. Most of the interest in the extreme risks in real estate has been reflected in papers that study the volatility of REITs but not how this volatility can help us better understand the volatility of the direct real estate markets.

For example, Lu et al. (2012) examine the diversification effects across international REITs and find that U.S. REITs contribute to most of the risks within international REITs. Moreover, Zhou and Anderson (2012) explore extreme risks in REITs and find that they tend to be higher than those of stocks. Other papers providing tools to better understand the risks of REITs include Springer and Cheng (2006), Pagliari et al. (2005) and Riddiough et al. (2005). We contribute to this literature by disentangling the direct real estate risk from the REIT risk, which could have potential implications for practitioners who wish to improve their understanding and management of real estate risk.

Model

We propose a simple model to better understand the risk of the real estate asset class, building on the work documented in Schlumpf and Tessera (2010). This model is based on two pillars: 1) a risk factor analysis of REIT returns, and 2) a simple accounting identity that relates REIT returns with direct real estate returns. Combining the first and the second pillars, we are able to perform a risk factor analysis of direct real estate that is useful for practical risk management considerations. This section explains in detail how our simple model works and how it can be easily applied to practical problems.

Our purpose is to estimate the risk factor exposures of the direct real estate. We would, therefore, like to produce estimates for the beta exposures of following equation:

$$r_{direct} = \alpha_{direct} + \Sigma_i \beta_{direct.i} f_i + \varepsilon_{direct} \quad (1)$$

Where r_{direct} represents the returns on direct real estate, α_{direct} represents the alpha returns on direct real estate, $\beta_{direct.i}$ represents the beta exposures of direct real estate to factor i, with f_i being the factor considered and εdirect representing the shocks to direct real estate returns.

Since direct real estate data presents several problems, as we argued in the previous section, the estimates for $\beta_{direct.i}$ that we can achieve using this data can be strongly biased, leading to wrong risk predictions. Nevertheless, given that REITs are listed on major exchanges and traded continually, there is enough availability of indirect real estate data that allows us to produce consistent and efficient estimates for the following equation:

$$r_{indirect} = \alpha_{indirect} + \Sigma_i \beta_{indirect.i} f_i + \varepsilon_{indirect} \quad (2)$$

Where $r_{indirect}$ represents the returns on indirect real estate, $\alpha_{indirect}$ represents the alpha returns on indirect real estate, $\beta_{indirect.i}$ represents the beta exposures of indirect real estate to factor i, with f_i being the factor considered and $\varepsilon_{indirect}$ representing the shocks to indirect real estate returns.

We estimate $\beta_{indirect.i}$ using a simple OLS approach in which the main factors under consideration are equities, fixed income, and credit. We can then go from (1) to (2) by considering the characteristics of REITs' balance sheets. Indeed, REITs are portfolios of direct property investments financed by mortgages or bonds.

Taking this information into account, we can show that once we have modeled the behavior of indirect real estate using time series data on REITs' returns (equity in the graph), we can approximate the behavior of direct real estate (property holdings in the graph) by taking into account the behavior of the debt of REIT companies. Indeed, since the returns on direct real estate is the sum of indirect real estate returns and debt returns weighted by the amount of leverage, i.e.,

$$r_{direct} = r_{indirect}(1 - lev) + r_{debt}(lev) \quad (3)$$

we can recursively use our risk factor model for REITs of equation (2) to show that the following relationships hold:

$$\beta_{direct} = \beta_{indirect}(1 - lev) + \beta_{debt}(lev) \quad (4)$$

$$dur_{direct} = dur_{indirect}(1 - lev) + dur_{debt}(lev) \quad (5)$$

$$\varepsilon_{direct} = \varepsilon_{indirect}(1 - lev) + \varepsilon_{debt}(lev) \quad (6)$$

Consequently, with data on each market's leverage and duration we can calculate $\beta_{indirect.i}$, i.e., the risk factor exposures of direct real estate. With unbiased estimates of $\beta_{indirect.i}$, we are then be able to express direct real estate in terms of f_i, build predicted time series, and, in this way, have a better understanding of direct real estate risk.

Data

We analyze six local indirect real estate indices for the markets of Australia, Canada, Switzerland, E.U., U.K. and U.S. Each REIT index (REITAULC, G250CALC, DBCHREF, EPEU, G250GBLC, and REITUSLC, respectively) represents the returns of a set of public real estate companies belonging to each particular market. In order to cover a full economic cycle, we consider the timeframe from January

1994 (February 1995 for Switzerland) to July 2012. Appendix A shows the details of the time series used in each case and Table 1 shows their summary statistics.

The leverage figures that we consider, shown in Table 2, have been calculated bottom-up by looking up all the annual reports of the REITs in the indices used.[1] It has been found that the funding duration is quite constant over time at the index level.

For each of the REIT indices that we consider, we propose relevant factors to estimate our OLS regression. Each model consists of six factors (See further data details in Appendix A): local equity index, world equity index (MSCI world), local short term fixed income (1-3 year maturity), local medium term fixed income (5-7 year maturity), local long term fixed income (10+ year maturity) and credit.

In order to compare the risk of the real estate asset class implied by our model with that of direct real estate indices, we take into account data of direct real estate in the UK, using the IPD index. We choose this market because it presents the longest time series available and also has a relatively good periodicity, as it is available on a monthly basis.

Results

Factor risk modeling

The results of the OLS regressions on indirect real estate indices are summarized in Table 3 and further details can be found in Appendix B. The different exposures across countries can partially be explained by the different sector splits in the REIT indices used for our analysis. Table 3 also reports the REIT duration that can be derived using the exposure of each series to the relevant fixed income time series and the respective EFFAS duration.

As in Schlumpf and Tessera (2010), we tested for multicollinearity in the regression design matrix (i.e., the independent variables), using the variance inflation factor (VIF).[2] None of the estimated regression coefficients showed multicollinearity.

	AU	CA	CH	EU	UK	US
Mean	0.005	0.007	0.005	0.003	0.004	0.009
Standard deviation	0.045	0.051	0.022	0.045	0.061	0.063
Median	0.008	0.013	0.005	0.006	0.007	0.016
Kurtosis	6.727	4.211	0.838	5.410	3.040	10.982
Skewness	-1.446	-0.759	-0.048	-1.135	-0.662	-1.749
Minimum	-0.259	-0.238	-0.068	-0.258	-0.265	-0.392
Maximum	0.146	0.212	0.083	0.146	0.222	0.268
Observations	222	222	210	210	222	222

Table 1: Summary statistics

Market	Leverage (%)	Debt duration	Index (Bloomberg ticker)
AUD	28.6	1.5	REITAULC
CAD	64.6	5.0	G250CALC
CHF	13.4	3.1	DBCHREF
EUR	46.7	3.5	EPEU
GBP	44.3	7.9	G250GBLC
USD	52.3	3.8	REITUSLC

Table 2: Leverage and duration

	AU	CA	CH	EU	UK	US
Local equity	0.63[a]	0.56[a]		0.43[a]	0.81a	
Global equity			0.16[a]			0.51[a]
FI 1-3			1.80[b]			
FI 5-7	0.73[a]	0.68[a]		0.20		0.57[b]
FI 10-30					0.32[b]	
Credit	1.15[b]			2.08[a]		4.51[a]
Residual volatility	11.9%	14.8%	6.9%	11.9%	17.2%	16.6%
Duration	3.8	3.7	3.6	1.1	5.1	3.2

Table 3: Regression summary – indirect real estate modeling
Significance at the 1% confidence level is denoted with "a," and significance at the 10% confidence level is denoted with "b".

	AU	CA	CH	EU	UK	US
Local equity	45.0%	20.0%		23.0%	45.3%	
Global equity			13.6%			24.5%
FI 1-5	6.0%	7.0%	56.0%	74.0%		39.0%
FI 5-10	49.0%	73.0%	30.4%	3.0%	26.0%	36.5%
FI 10-30					28.7%	
Credit	82.2%			111.0%		215.2%
Residual volatility	8.5%	5.2%	6.0%	6.4%	9.6%	7.9%
Duration	3.2	4.5	3.5	2.2	6.4	3.5

Table 4: Regression summary – direct real estate modeling

1 We are grateful to Stefan Weber, Ramona Reinert, and Philipp Langenegger for providing us with this data.
2 The VIF is derived from the variance of the estimated regression coefficients and tells us how much the variance of the estimated coefficient is "inflated" by the existence of correlation among the predictor variables in the model.

Using our figures for leverage and duration and applying our simple model, we achieve the estimation of the exposures of direct real estate returns summarized in Table 4. In particular, we use equation (4) for the beta coefficients of local equity, global equity and credit. For the residual volatility, we use equation (6). In addition, for fixed income we consider coefficients that would add up to 100% leaving credit as an overlay, and seek to distribute the fixed income exposures in order to comply with equation (5), while using the respective EFFAS durations.

The duration figures that we calculate for direct real estate are in line with the estimations of the recent literature. Indeed, several papers show that real estate has low interest rate sensitivity [Rauh and Rieder (2004); Iacoviello (2000); Sutton (2002); Tsatsaronis and Zhu (2004)]. This applies also for the Swiss market, as it is argued by Constantinescu (2009).

Market risk estimation

We would now like to use these results to achieve a better understanding of risk in the real estate markets. In this sense, we would like to be able to provide some explanation of extreme events such as the one depicted in Figure 1, and to provide insights about the implications on risk management.

We use the results of our direct real estate model reported in Table 4 and build a predicted series. This allows us to compare our model with the traditional approaches, as we can compare the behavior of this predicted series with that of traditional direct real estate series. We do this exercise using data from the U.K.

We find that the volatility of the predicted series for the studied period is 11.9%. This is considerably higher than the volatility of the simple IPD U.K. appraisal-based index for the same period, which is 4%. Consequently, with our modeled direct real estate time series we are able to make extreme events, such as the one depicted in Figure 1, not so extreme, as they would correspond to a 2 standard deviation move, and not to a 5 standard deviation move. Indeed, this kind of events could be expected under a fat tail distribution.

According to the model proposed by Devaney and Martinez Diaz (2010), the volatility of the transaction-based index that they propose, which is based on the same IPD data for the U.K. that we consider, is 6.3% for the period between Q1 2002 and Q2 2009. Even if this volatility is higher than the IPD appraisal-based data, it is almost half of our estimation, which implies that this methodology would still considerably underestimate risk. Moreover, if we consider the same time frame as these authors do, then our result is even higher and equal to 12.2%.

Furthermore, we also take into account the volatility that would result from the common practice of unsmoothing direct real estate data by considering an autocorrelation parameter. We find that this volatility will be much higher than the one predicted by our model. Indeed, for the period under study it would be 16.8%. This reflects the findings of Bond et al. (2006), who argue that the autocorrelation filter tends to overstate the smoothing taking place in direct real estate data.

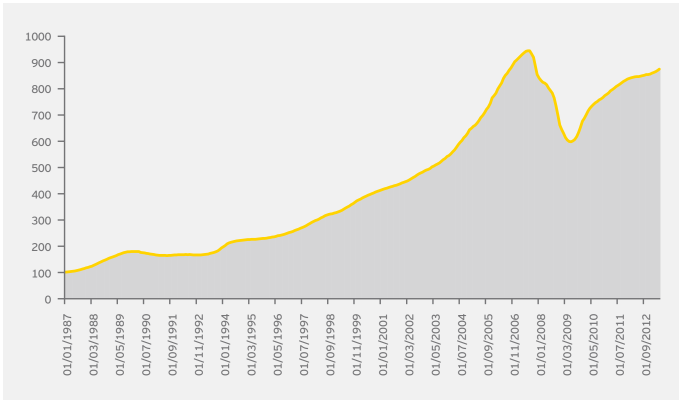

Figure 1: Extreme event in the U.K. direct real estate market (IPD)
Source: Bloomberg

				Model comparison		
	EQ	FI 5-10	FI 10+	RE IPD	RE model	IPD filter
EQ	1					
FI 5-10	-0.14	1				
FI 10+	-0.07	0.89	1			
RE IPD	0.15	-0.15	-0.02	1		
RE model	0.58	0.21	0.24	-0.05	1	
IPD filter	0.05	-0.17	-0.11	0.44	-0.12	1
Volatility	14.4%	4.7%	7.9%	4.0%	11.9%	16.8%

Table 5: Volatility and correlations comparison

These empirical results indicate that our approach proposes a middle-way solution, which does not suffer from the problems of the autocorrelation filter, but is still able to provide a higher volatility for the real estate market. Moreover, we find that both unfiltered and filtered direct real estate data present negative correlations with fixed income in the short- and long-run, while our model predicts positive correlations, as can be seen in Table 5. In this sense, our results are similar to those of Solvency II. Indeed, according to the fifth Quantitative Impact Study (QIS 5) for Solvency II, the volatility for equities is 15.5% and for real estate it is 9.7%, with a correlation of 0.75 between the two.

We also consider a representative portfolio that allocates 25% to real estate, 25% to equity, 30% to short-term fixed income and 20% to long-term fixed income, to see how these findings would affect overall portfolio risk. As can be seen in Table 6, we find that when we consider direct real estate IPD indices, the volatility of the portfolio is the lowest at 4.6%. Using the autocorrelation filter leads to a result of 5.9%. Finally, when we consider our modeled real estate series we have a higher portfolio risk, amounting to 6.7%.

The fourth row of Table 6 shows how our model can be implemented and used in vendors' risk systems that cover equities and fixed income as an asset class, but do not cover direct real estate. Indeed, our model can easily be implemented in a simple two-step process: 1) In a portfolio of equities and fixed income, add to each of these asset classes the direct real estate exposures to those asset classes resulting from our model. 2) Add the residual risk of real estate as an idiosyncratic risk.

For our U.K. example, in the first step we do the following: to the 25% equity, the 30% of 1-5 fixed income and the 20% of 10+ fixed income, we add the 25% of real estate allocation multiplied by the exposures of the direct regression for U.K. This gives an allocation to EQ of 36.3%, to FI 5-10 of 36.5% and to FI 10+ of 27.2% and results in a portfolio volatility of 6.1%. By adding the residual volatility of 9.6% with a weight of 25% and zero correlation we get a higher portfolio volatility, close to the one of the direct calculation.

Conclusion

We show that direct real estate can be thought of as a portfolio of equities, fixed income and credit combined with idiosyncratic risk. The composition of this portfolio is derived by regressing REITs data and deleveraging the resulting asset exposures according to the leverage in the considered REITs. Following this simple model, the market risk for direct real estate is higher than that of appraisal or transaction-based data. Moreover, the correlations to risky assets are higher in our model than in the appraisal-based models. This is important for both risk management and asset allocation. Further studies could consider more countries and analyze the impact of the different real estate sectors.

EQ	FI 5-10	FI 10+	RE IPD	IPD filter	RE model	Volatility
25%	30%	20%	25%			4.6%
25%	30%	20%		25%		5.9%
25%	30%	20%			25%	6.7%
36.3%	36.5%	27.2%				6.1%

Table 6: Representative portfolios' volatility comparisons

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Appendices

A. Data description

The following data series are used as the explanatory variables in the regressions: MSCI equity indices and local equity indices, EFFAS government bond indices for fixed income, and credit spread data based on CDS investment grade index (5 years) for credit.

Fixed income	1-3 years	XXG1TR index	with XX= SZ, EU, US, UK, AU or CA
	3-5 years	XXG2TR index	
	5-7 years	XXG3TR index	
	7-10 years	XXG4TR index	
	10+ years	XXG5TR index	
Equities	MSCI World	GDDUWI index	in USD and translated to the other currencies
	Swiss Performance index	SPI index	for SZ
	Euro Stoxx	SXXE index	for EU
	S&P500	SPX index	for US
	FTSE 100	UKX index	for UK
	ASX 200	AS51 index	for AU
	TSX	SPTSX index	for CA
Credit		IBOXUMAE index	EDSISP index before 2003

Table A1: The specific Bloomberg tickers

B. Regression details

Australia – REITAULC index				
	Coefficient	Standard error	t-ratio	p-value
Constant	-0.001	0.003	-0.340	0.735
ASX	0.631	0.073	8.586	0.000[a]
FI_m	0.732	0.169	4.323	0.000[a]
Credit	1.151	0.561	2.053	0.000[b]
Mean dependent variable	0.005	S.D dependent variable		0.044
Sum squared residual	0.260	S.E. of regression		0.035
R-squared	0.404	Adjusted R-squared		0.396
F(3,218)	49.318	P-value (F)		0.000
Log-likelihood	434.110	Akaike criterion		-860.220
Schwarz criterion	-846.609	Hannan-Quinn		-854.725
Rho	0.060	Durbin-Watson		1.873

OLS, using observations 1994:02-2012:07 (T=222); significance at the 1% confidence level is denoted with a, and significance at the 10% confidence level is denoted with b.

Canada – G250CALC index				
	Coefficient	Standard error	t-ratio	p-value
Constant	0.001	0.003	0.292	0.771
TSX	0.565	0.062	9.110	0.000[a]
FI_m	0.680	0.231	2.948	0.004[a]
Mean dependent variable	0.007	S.D dependent variable		0.051
Sum squared residual	0.401	S.E. of regression		0.043
R-squared	0.295	Adjusted R-squared		0.289
F(3,218)	45.856	P-value (F)		0.000
Log-likelihood	386.000	Akaike criterion		-766.001
Schwarz criterion	-755.793	Hannan-Quinn		-761.879
Rho	0.168	Durbin-Watson		1.655

OLS, using observations 1994:02-2012:07 (T=222); significance at the 1% confidence level is denoted with a, and significance at the 10% confidence level is denoted with b.

Switzerland – DBCHREF index				
	Coefficient	Standard error	t-ratio	p-value
Constants	0.005	0.002	2.154	0.032[b]
MSCI	0.157	0.031	5.142	0.000[a]
cash	-3.433	1.607	-2.136	0.340[b]
FI_short	1.800	0.381	4.727	0.000[a]
Mean dependent variable	0.005	S.D dependent variable		0.044
Sum squared residual	0.083	S.E. of regression		0.035
R-squared	0.177	Adjusted R-squared		0.396
F(3,218)	14.746	P-value (F)		0.000
Log-likelihood	525.053	Akaike criterion		-860.220
Schwarz criterion	-1028.717	Hannan-Quinn		-854.725
Rho	-0.112	Durbin-Watson		1.873

OLS, using observations 1995:02-2012:07 (T = 210); significance at the 1% confidence level is denoted with a, and significance at the 10% confidence level is denoted with b.

European Union — EPEU index				
	Coefficient	Standard error	t-ratio	p-value
Constant	0.000	0.003	0.190	0.850
SXXE	0.432	0.051	8.488	0.000[a]
FI_m	0.201	0.224	0.897	0.371
credit	2.083	0.552	3.775	0.000[a]
Mean dependent variable	0.002	S.D dependent variable		0.046
Sum squared resid	0.262	S.E. of regression		0.035
R-squared	0.442	Adjusted R-squared		0.434
F(3,218)	57.531	P-value (F)		0.000
Log-likelihood	433.195	Akaike criterion		-858.390
Schwarz criterion	-844.779	Hannan-Quinn		-852.895
Rho	0.185	Durbin-Watson		1.628

OLS, using observations 1994:02-2012:07 (T=222); significance at the 1% confidence level is denoted with a, and significance at the 10% confidence level is denoted with b.

United Kingdom — G250GBLC index				
	Coefficient	Standard error	t-ratio	p-value
Constant	0.000	0.003	-0.089	0.929
UKX	0.814	0.080	10.198	0.000[a]
FI_long	0.318	0.142	2.237	0.026[b]
Mean dependent variable	0.003	S.D dependent variable		0.061
Sum squared residual	0.542	S.E. of regression		0.050
R-squared	0.332	Adjusted R-squared		0.326
F(3,218)	54.388	P-value (F)		0.000
Log-likelihood	352.630	Akaike criterion		-699.259
Schwarz criterion	-689.051	Hannan-Quinn		-695.138
Rho	0.081	Durbin-Watson		1.835

OLS, using observations 1994:02-2012:07 (T=222); significance at the 1% confidence level is denoted with a, and significance at the 10% confidence level is denoted with b.

United States — REITUSLC index				
	Coefficient	Standard error	t-ratio	p-value
Constant	0.005	0.003	1.498	0.136
MSCI	0.514	0.089	5.744	0.000[a]
FI_m	0.568	0.243	2.332	0.021[b]
Credit	4.508	0.823	5.481	0.000[a]
Mean dependent variable	0.009	S.D dependent variable		0.063
Sum squared residual	0.505	S.E. of regression		0.048
R-squared	0.418	Adjusted R-squared		0.410
F(3,218)	52.150	P-value (F)		0.000
Log-likelihood	360.567	Akaike criterion		-713.134
Schwarz criterion	-699.523	Hannan-Quinn		-707.638
Rho	-0.033	Durbin-Watson		2.060

OLS, using observations 1994:02-2012:07 (T=222); significance at the 1% confidence level is denoted with a, and significance at the 10% confidence level is denoted with b.

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ISSN 2049-8640