DOWNSIDE BETA AND VALUATION-BASED PROPERTY RETURNS

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ABSTRACT

This study aims to examine the ability of downside beta in explaining the Australian direct property returns with addressing the smoothing issue. Utilising the quarterly IPD/PCA Australian property indices over 1995-2008, the results reveal that smoothed and unsmoothed downside betas are statistically distinguishable. The results also show that unsmoothed downside beta is positive and statistically significant related to Australian direct property returns, while smoothed downside beta exhibits a negative link with the returns, indicating that appraisal-smoothing has profound implications on the efficiency of downside beta. The results are robust after controlling for the different types of property and different smoothing parameters, confirming that a positive premium is required by direct property investors for compensating higher downside losses. These findings provide further insights into the pricing of valuation-based property indices.

Keywords: Direct property, downside beta, smoothing, Australia

INTRODUCTION

The Australian direct property market is one of the largest direct property markets in the world. In 2006, it was ranked as the 9th largest direct property market (RREEF, 2007). Property and business services[1] sector was also the most important industry, contributing approximately 11% of the Australian GDP in 2005-2006 (ABS, 2008). More importantly, the Australian property market was ranked as the second most transparent property market in the world (JLL, 2008).

Direct properties in Australia also have significant levels of institutional investor involvement. Higgins (2007) estimated that more than 70% of core property in Australia are owned by institutional investors. In 2008, almost 70% of investment grade properties in Australia are in securitised form and owned and/or managed by listed and unlisted funds (PIR, 2008). The significant involvement of institutional investors has also highlighted the importance of a greater understanding of direct properties, particularly the pricing of direct properties.

[1] It should be noted that this sector does not include ownership of dwellings.

Although the Capital Asset Pricing Model (CAPM) is the most established asset pricing model in the finance and real estate literature, the empirical support of the model is limited (Fama and French, 2004). The empirical support of the CAPM generally follows strict assumptions. The CAPM assumes that (1) investors view upside gains and downside losses in the same manner, (2) all investors are risk averse with a constant quadratic utility function assumption and (3) return distributions must be normally distributed.

Importantly, these assumptions have been rejected by many empirical and analytical studies (Pratt, 1964; Arrow, 1971; Myer and Webb, 1993, 1994). In response to the weak empirical support of CAPM, extensive studies have demonstrated the importance of employing Lower Partial Moment-CAPM to capture the asymmetry in returns and downside beta is argued as a favourable risk measure in asset pricing. This has been explained by the behaviour of investors in which a premium is only required to compensate higher downside losses. More specifically, downside risk is the only risk of investors, while upside gain should be viewed as upside potential rather than risk. Similar empirical evidence of downside beta has been demonstrated by Cheng (2005) in the US direct property market.

It must be noted that direct property returns are valuation-based returns and the values are not derived from market transactions. This issue is commonly referred to as appraisal-smoothing bias in the real estate literature. Numerous real estate studies have also demonstrated that the smoothing bias is present in many valuation-based real estate indices and its consequences are severe (Geltner *et al.*, 2003). Although this issue has also been widely recognised by real estate researchers and practitioners, the issue of smoothing is largely ignored by downside risk studies. Therefore, this study aims to address this gap by examining the ability of downside beta in explaining direct property returns with considering the impacts of smoothing.

The contributions of this study are two-hold. First, the smoothing bias in direct property returns is adjusted for the first time in assessing the efficiency of downside beta. No smoothing issue is taken into consideration in previous real estate studies in examining the explanatory power of downside beta in explaining direct property returns, although the smoothing issue has appeared as a serious issue in the valuation-based real estate returns. Second, this is the first study of downside beta in the Australian direct property context. The Australian direct property context provides another dataset for examining the efficiency of downside beta in valuation-based real estate returns and offers a comparison to the U.S. direct property market.

The remainder of this paper is structured as follows. Section 2 reviews the related literature of downside beta and smoothing. Section 3 discusses the data and methodology of this study. The results are reported and discussed in Section 4. Last section concludes the paper.

LITERATURE REVIEW

Lower Partial Moment-CAPM (LPM-CAPM) has become increasingly accepted in respect to its empirical support (Estrada, 2002; Ang et al., 2006). Unlike the CAPM, the LPM-CAPM posits that downside beta rather than conventional beta as the risk measure in asset pricing. There are several rationales of using LPM-CAPM (or downside beta): (1) it does not require any assumption on the asset return distribution, (2) it is more consistent with investors' utility functions, (3) it is the model that focusing on downside part in which it considers the market conditions and incorporates the distinctive between downside and upside variability in asset pricing (Hogan and Warren, 1974; Bawa and Linderberg, 1977). Therefore, the LPM-CAPM appears as a more intuitively appealing pricing model for investors and portfolio managers.

Extensive empirical evidence of the CAPM (or beta) and LPM-CAPM (or downside beta) are individually identified is also available in the literature. Nantell *et al.* (1982) and Price *et al.* (1982) found that traditional beta and downside beta are empirical distinguishable if the asset return distributions are not normally distributed. In the real estate context, Lee *et al.* (2008c) documented comparable results and confirmed that both betas are empirically distinguishable. The study also found that downside beta and traditional beta of REITs (formerly known as LPTs) have different determinants. More recently, Galagedera (2007) provided evidence of the linkages between betas and downside betas are strongly influenced by the return distribution characteristics of an asset.

Importantly, numerous studies have also demonstrated the efficiency of downside beta over traditional beta. Pedersen and Hwang (2003) found that downside beta has higher explanatory power to U.K. equity returns, although it fails to improve the asset pricing model considerably. Estrada (2002) also offered empirical evidence of downside beta is an efficient risk measure and it outperforms traditional beta in explaining the returns of emerging stock markets. Estrada and Serra (2005) also revealed that global downside beta is the most important factor in explaining the cross-sectional returns of emerging stock markets. Post and Vilet (2004) and Ang *et al.* (2006) demonstrated the empirical evidence in favour of LPM-CAPM in the U.S. stock market. Similar results are also demonstrated by Lee *et al.* (2008b) in the REIT market and Cheng (2005) in US direct property. These studies confirmed that a risk premium is required for higher downside beta by investors, whereas no premium is expected for upside beta.

The efficiency of downside beta can be attributed to the consistency of downside beta with investors' risk perception. Kahneman and Tversky (1979) and Gul (1991) argue that investors are more concerned with downside losses in light of the impacts of downside losses are far greater than upside gains. Ang *et al.* (2006) also provided analytical evidence of investors only require a reward for downside losses. A recent survey of property fund managers further confirmed that downside risk is consistent with how investors individually perceive risk, and a downside premium is expected for higher downside losses by investors (Lee et al., 2008a).

Despite extensive studies that have demonstrated the efficiency of downside beta in stock and REIT asset pricings, there is little work that has been placed on direct property returns. One exception is the study of Cheng (2005). Additionally, no attempt has been directed to examine the impacts of smoothing bias on the efficiency of downside beta, although there is a consensus that failure to account for the smoothing bias in valuation-based real estate returns may lead to incorrect statistical inferences. Consequently, it would have profound implications on real estate risk and portfolio management.

Liu *et al.* (1990) pointed out the impact of smoothing on the performance of real estate. They found that the superior performance of real estate could be caused by the smoothing bias. Importantly, the smoothing in valuation-based returns has also engendered the underestimation of actual risk (Geltner, 1993). Lai and Wang (1998), on the other hand, found contradictory results where an overestimation of risk in appraisal-based real estate returns is presented. More recently, Edelstein and Quan (2006) compared valuation-based and transaction-based returns of individual properties and found that the smoothing bias not only dampens the volatility of direct property, but also the returns. Miles *et al.* (1990) also demonstrated the impact of smoothing on property portfolio allocation. Marcato and Key (2005) also found an alteration for their findings of momentum strategy in the U.K. direct properties when the issue of smoothing is addressed. More importantly, Geltner (1989) has offered empirical evidence of divergence beta results from uncorrected and corrected smoothing bias in real estate returns. Interestingly, the beta of direct property with respect to stock market is negative, while a positive beta is documented once the smoothing bias is corrected.

In summary, even though numerous studies have demonstrated the significance of downside beta in explaining returns, the impact of smoothing on downside beta in explaining a valuation-based real estate return series is limited.

DATA AND METHODOLOGY

Data

The data utilised in this study consists of quarterly returns of direct properties over Q3:1995-Q2:2008. The data were extracted from IPD/PCA. This study commenced from Q3:1995 since quarterly data is only available after Q3:1995. 87 Australian property sectors were assessed:

- Total property: IPD/PCA Composite Index
- Property sub-sectors: office, retail, industrial property
- Office property grades: Premium, Grades A, B, C and D
- Office property sizes: <7,500m^2, 7,500-15,000m^2, 15,000-30,000m^2 and >30,000m^2
- Office property regions: CBD, non CBD, Sydney, Melbourne, Brisbane, Perth,

Adelaide, Canberra, Lower North Shore, North Ryde and Parramatta, and rest of Sydney

- Retail property types: super and major regional, regional, sub-regional, neighbourhood retail, bulky goods retail, other
- Retail property sizes: < 30,000m^2, 30,000-50,000m^2 and >50,000m^2
- Retail property regions: New South Wales, Victoria, Queensland, Western Australia, South Australia, metropolitan centres and country centres
- Industrial property types: high tech, unit estate, warehouse, warehouse prime, warehouse secondary and distribution
- Industrial property sizes: <7,000m^2, 7,000-12,000m^2, 12,000-25,000m^2 and >25,000m^2
- Industrial property values: < \$6million, \$6-\$11million, \$11-\$20million, >\$20million
- Industrial property regions: Sydney, Melbourne, Brisbane, Sydney Central West, Sydney North, Sydney Outer West and Sydney South and rest of Australia.

Note that the IPD/PCA Total Property Composite Index was used as the proxy for the market, where the proxy for the risk-free rate was the one month interbank rate. The data of 1-month interbank rate were obtained from DataStream. The summary statistics of direct properties are reported in Table 1.

Table 1: Summary statistics of direct property quarterly returns: Q3:1995-Q2:2008

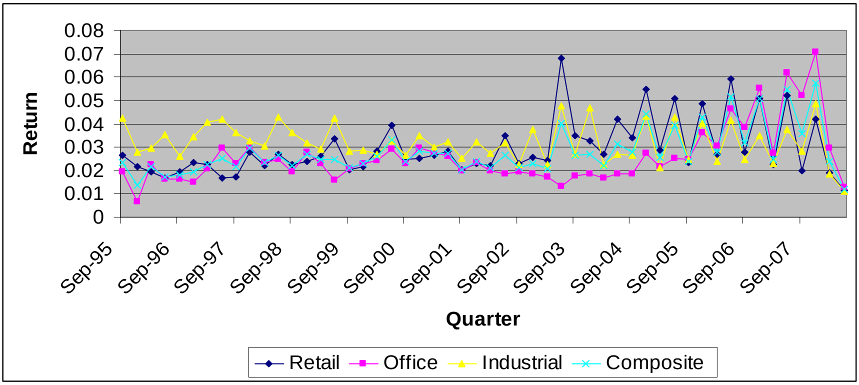
Statistics	Composite Property	Retail	Office	Industrial
Mean	2.851	3.006	2.632	3.307
Standard Deviation	0.983	1.191	1.228	0.912
Skewness	1.440	1.369	1.819	1.281
Kurtosis	4.377	4.147	6.395	5.867
Count	52	52	52	52

As depicted in Table 1, the return of composite property over this study period was around 2.9% per quarter with the standard deviation of 0.98%. Industrial property has been the best performed property sector with the average return of 3.3% per quarter, compared to retail property (3%) and office property (2.6%). Importantly, the standard deviation statistics have reinforced the significance of industrial property in Australia in which industrial property was the sector with the lowest risk level (0.912%), whereas office property being the most volatile property sector (1.228%) over 1995-2008 in Australia.

This significance of Australian industrial property has also been assessed by Newell (2007).

The skewness statistics also show that these return distributions are positively skewed, suggesting that the downside variability of these sub-sectors is higher than the upside. These also indicate that the return distributions of direct properties (including office, retail and industrial) are asymmetrically distributed. In addition, the usual feature of excess kurtosis is also observed for all series from Table 1, being most pronounced for the office series. These statistics imply that the distributions of direct properties are in asymmetrical form. These also provide some indirect evidence to support the appropriateness of employing downside beta in Australian direct properties.

Figure 1: Time series plot for composite, office, retail and industrial properties quarterly returns



Notes: This figure plots for the quarterly return movements in composite, office, retail and industrial properties.

Figure 1 plots the time series movements in quarterly returns of composite, office, retail and industrial properties. As shown in Figure 1, the movements in these sectors are consistent with similar turning points. This suggests that the presence of similarities in behaviour over time for these series. Moreover, the movements in the series appear smooth and flat, particularly over the study period of Q3:1997-Q3:2002, suggesting that these markets were stable and less volatile. However, the true volatility of these markets could be largely underestimated in which these are valuation-based real estate indices.

Methodology

It should be noted that the IPD/PCA Australia property indices are valuation-based indices. Therefore, the Geltner (1993) smoothing correction method was employed to desmooth direct property returns. As demonstrated by Geltner (1993):

$$R_t^* = WR_t + (1-W)R_{t-1}^* \tag{1}$$

where W is the smoothing parameter, R_t^* is the current valuation-based return, R_{t-1}^* is the previous valuation-based return and R_t is the contemporaneous transaction-based return. In this study, the smoothing parameter of 0.2 was selected. This implies that the new information will only be incorporated annually, and the average lag is equal to one year. This is also consistent with Fisher and Geltner (2000) and Bond and Hwang (2003).

Once unsmoothed returns are computed, both smoothed and unsmoothed returns series are employed to compute the downside betas of direct properties. Three common measures of downside beta (Bawa and Linderberg, Harlow and Rao and Estrada) have been proposed in the literature. However, recently, Galagedera (2007) has highlighted the importance of choosing an appropriate downside beta definition for an asset. His empirical results showed that Bawa and Linderberg (1977) definition of downside beta emerges as a preferable definition when only assets have abnormal returns or high volatility. On the other hand, the Harlow and Rao (1989) definition is a better downside systematic risk measure for asset return distribution with high kurtosis. The efficiency of Estrada (2002) definition depends on a function of the market portfolio returns and the asset returns. All of these highlight that the characteristics of an asset distribution may lead to different downside beta conclusions.

Thus, in this study, three common measures of downside beta are employed in order to assess the efficiency of downside beta critically and avoid misleading conclusions due to misspecification of downside beta estimation procedures. These definitions are written as follows:

Bawa and Linderberg (1977) downside beta definition $\left(DB_i^{BL}\right)$ is given:

$$DB_i^{BL} = \frac{E\{(R_i - R_f)Min[(R_m - R_f),0]\}}{E\{Min[(R_m - R_f),0]^2\}} \tag{2}$$

where R_f is the risk-free rate of return, R_m is the market return and R_i is the return of asset i.

Harlow and Rao (1989) suggested that the mean returns are more relevant in asset pricing and defined downside beta $\left(DB_i^{HR}\right)$ as follows:

$$DB_i^{HR} = \frac{E\{(R_i - \mu_i) Min[(R_m - \mu_m), 0]\}}{E\{Min[(R_m - \mu_m), 0]^2\}} \tag{3}$$

where μ_i and μ_m is the average returns of asset i and market average returns respectively.

More recently, Estrada (2002) formally defined downside beta (DB_i^E) as follows:

$$DB_i^E = \frac{E\{Min[(R_i - B_i), 0] Min[(R_m - B_m), 0]\}}{E\{Min[(R_m - B_m), 0]^2\}} \tag{4}$$

where B_i and B_m are the benchmark for asset i and market respectively. Estrada (2006) suggested that three different cut-off points (mean, risk-free rate and zero return) can be applied to this measure. Importantly, the results also exhibit that divergence results can be obtained by using these different cut-off points. As such, these benchmarks: mean return ($DB_{i,M}^{(E)}$), risk-free rate ($DB_{i,Rf}^{(E)}$) and zero target rate ($DB_{i,Z}^{(E)}$) are utilised in this study in order to examine the robustness of the empirical results.

The explanatory power of downside beta in explaining the cross sectional variations of direct property returns is examined by using the following cross-sectional regression:

$$E(R) = \alpha + \gamma(RV) + \varepsilon \tag{5}$$

$E(R)$ is the average return of properties, α is the intercept, RV denotes the downside betas (including DB_i^{BL}, DB_i^{HR}, $DB_{i,M}^E$, $DB_{i,Rf}^E$ and $DB_{i,Z}^E$), ε represents the error term. In other words, 5 individual models are constructed by using these 5 different downside beta measures respectively. A similar procedure is also employed by Estrada (2002) and Cheng (2005).

RESULTS AND DISCUSSION

The normality tests (namely Jarque-Bera, Lilliefors and Shapiro-Wilk tests) are first undertaken with respect to the preliminary asymmetry evidence of direct properties that is manifested by skewness and kurtosis. Most importantly, recent studies have highlighted the importance of understanding the property return distributions where downside beta is an efficient risk measure if only returns are asymmetrically distributed. The results are reported in Table 2.

Table 2: Normality tests

Tests	Jarque-Bera Test	Lilliefors Test	Shapiro-Wilk Test
Percentage of Rejected Number Sub-sector over the Sample with 10% Significance Level*	94.253%	91.954%	98.851%
Percentage of Rejected Number Sub-sector over the Sample with 5% Significance Level	89.655%	86.201%	97.701%
Percentage of Rejected Number Sub-sector over the Sample with 1% Significance Level	87.356%	68.966%	85.058%

Notes: This table presents the results of Jarque-Bera, Lilliefors and Shapiro-Wilk tests for normality.
*These figures are the percentage of direct property sub-sectors in the sample that are rejected by normality tests.

A number of points are noted from Table 2. Firstly, being consistent with the preliminary results, there is no evidence to support these return distributions are normally distributed. Almost 86% of the sample has been rejected by Jarque-Bera, Lilliefors and Shapiro-Wilk tests at the 5% significance level. Interestingly, 'Rest of Australia Retail' and 'NSW Retail sub region' are the only sectors that exhibit normal distributions. Possible explanation is these retail sectors are less influenced by economic events such as 'September 2001' in which Pedersen and Hwang (2003) argued that these events have far reaching implications on return distributions.

Higher asymmetric results are found by using Shapiro-Wilk test. One explanation for the higher asymmetric results with Shapiro-Wilk test is that the test is more sensitive to smaller sample size. In this study, the majority of the sub-sectors only has 52 observations, while Sydney CBD Office: Grade Premium and the Rest of Australia: Retail sectors have as little as 32 useable observations. In fact, Shapiro-Wilk test appears as the preferable normality test for these samples in respect to the small sample sizes (Marques de sa, 2003).

Similar asymmetry conclusions were also reached by Newell (1998) and Lee *et al.* (2008b) in Australian commercial property and LPTs and Myer and Webb (1993, 1994) in the U.S. property markets. These results provide support to the use of downside beta in measuring the systematic risk of direct properties.

Unsmoothed and smoothed downside betas

Table 3 displays the descriptive summary of smoothed and unsmoothed downside betas from Equations (2) to (4). Panel A of Table 3 presents the summary of downside betas without smoothing correction. $DB_{i,Z}^{(E)}$ provides the highest downside beta estimations of direct properties in which the average of downside betas is 1.362. On the other hand, $DB_{i}^{(BL)}$ exhibits the lowest level of average downside betas with 0.745. Importantly, the average of $DB_{i,Z}^{(E)}$ is almost double the mean of $DB_{i}^{(BL)}$. This can be attributed to the smoothing bias in which it has underestimated the actual risk levels of direct properties. As discussed by Galagedera (2007), $DB_{i}^{(BL)}$ is only suitable to be applied to asset returns with high volatility. Therefore, it is not surprising that smoothed downside beta with Bawa and Linderberg definition has been considerably underestimated. This has also addressed the importance of selecting an appropriate downside beta estimation in downside risk studies.

Table 3: Descriptive summary of downside betas

Downside betas	$DB_{i,M}^{(E)}$	$DB_{i,R_f}^{(E)}$	$DB_{i,Z}^{(E)}$	$DB_{i}^{(BL)}$	$DB_{i}^{(HR)}$
Panel A: Smoothed downside betas					
Mean	0.962	0.924	1.362	0.745	0.832
Median	0.862	0.880	1.214	0.735	0.866
Count	86	86	86	86	86
Panel B: Unsmoothed downside betas					
Mean	1.111	1.101	1.122	0.978	0.996
Median	1.055	1.041	1.068	0.951	0.950
Count	86	86	86	86	86

Notes: This table gives the summary statistics for the estimated downside betas. DB_{i}^{BL}, DB_{i}^{HR}, $DB_{i,M}^{E}$, $DB_{i,Rf}^{E}$ and $DB_{i,Z}^{E}$ represents the downside beta estimation of Bawa and Linderberg, Harlow and Rao, Estrada with respect to target rate of mean, Estrada with respect to target rate of risk-free rate and Estrada with respect to target rate of zero respectively.

Panel B of Table 3 exhibits the summary of unsmoothed downside betas. $DB_{i,Z}^{(E)}$ and $DB_{i}^{(BL)}$ reveal the highest and lowest downside beta estimations respectively, although the difference is marginal. Interestingly, $DB_{i,M}^{(E)}$, $DB_{i,R_f}^{(E)}$ and $DB_{i,Z}^{(E)}$ provide comparable results of downside beta estimations. Specifically, the average of these definitions are around 1.1. Similar results are also obtained from the median, indicating that different target rates of return do not have pronounced implications on the Estrada downside beta definition. The results are also consistent with the results from Lee *et al.* (2008b) in

Australian LPTs.

Another important observation is unsmoothed downside betas are larger in magnitude than smoothed downside betas, except $DB_{i,Z}^{(E)}$. The smoothing bias in the valuation- based index is the plausible reason for this finding in which numerous studies have demonstrated that smoothed returns underestimate the actual risk of direct properties (Geltner, 1993; Newell and MacFarlane, 1996). Therefore, it is reasonable to expect that downside betas after the smoothing correction would exhibit higher magnitudes than smoothed downside betas. This also signifies that the smoothing bias is a critical issue in direct properties in which unsmoothed downside beta appears to be underestimated and it is distinguishable from smoothed downside beta. In other words, the asset allocation of investors should be carefully examined in which the true volatility has been largely underestimated. Additionally, the validity of estimated expected returns for direct properties based on smoothed beta should also be evaluated rigorously in respect to the bias of appraisal-smoothing.

To reinforce the point further, unsmoothed and smoothed downside betas are formally compared by t-test (parametric) and sign-test (non-parametric). The results are depicted and discussed in Table 4.

Table 4: Comparison between smoothed and unsmoothed downside betas

Downside Betas	T-Test	Sign-Test
$DB_{i,M}^{(E)}$	2.555 (0.012)**	-3.774 (0.000)***
$DB_{i,R_f}^{(E)}$	3.884 (0.000)***	-3.990 (0.000)***
$DB_{i,Z}^{(E)}$	-2.095 (0.039)**	-0.323 (0.746)
$DB_{i}^{(BL)}$	4.007 (0.000)***	-3.343 (0.001)***
$DB_{i}^{(HR)}$	3.368 (0.001)***	-2.480 (0.013)**

Notes: This table reports the results of t-test and sign-test for testing the difference between smoothed and unsmoothed downside betas. DB_i^{BL}, DB_i^{HR}, $DB_{i,M}^{E}$, $DB_{i,Rf}^{E}$ and $DB_{i,Z}^{E}$ represents the downside beta estimation of Bawa and Linderberg, Harlow and Rao, Estrada with respect to target rate of mean, Estrada with respect to target rate of risk-free rate and Estrada with respect to target rate of zero respectively.
*, **, *** denotes significance at the 10%, 5%, 1% level respectively.

As shown in Table 4, t-statistics of these 5 downside beta measures are positive and statistically significant at least at the 5% level. The only exception is $DB_{i,Z}^{(E)}$ where the t-statistic is negative and significant at 5%. These strong and significant t-statistics indicate that smoothed and unsmoothed downside betas are statistically distinguishable and the downside beta of valuation-based real estate indices is substantially understated.

The sign tests provide similar results where z-statistics are negative and significant at 1% in general. These illustrate that both downside betas are empirically distinguishable. However, the z-statistics of $DB_{i,Z}^{(E)}$ is negative and statistically insignificant. The slight variation results between t-test and sign-test can be attributed to the nature of these different tests.

In short, both corrected and uncorrected downside betas are individually identified, indicating that downside betas of direct properties would appear to be underestimated. Hence, it might reasonably be hypothesised that the smoothing bias in valuation-based real estate indices would also affect the explanatory power of downside beta in direct property returns.

The efficiency of downside beta

The previous section finds the evidence of the smoothing bias engender an underestimation of downside beta for direct properties. This section seeks to examine the impact of smoothing on the significance of downside beta. The estimated results from Equation (5), which the ability of downside beta in explaining the cross sectional variations of direct property returns, are shown in Table 5. It should be noted that 5 models were constructed individually for 5 different definitions of downside beta.

It is clear from Panel A of Table 5 that downside beta coefficients are negative and statistically significant at 1%. These results are inconsistent with previous results in U.S. direct properties (Cheng, 2005) and Australian LPTs (Lee *et al.*, 2008b). The discrepancy between Cheng (2005) and this study could be attributed to different markets. Besides, a different method of constructing direct property indices between the two countries could also be plausible explanation. Another reason may simply be different study periods for these studies. Cheng (2005) utilised data over 1992-2002, whereas the study period of this study is from 1995-2008. Importantly, these also highlight that international evidence on the efficiency of downside beta in explaining valuation-based property returns should be provided.

Although different markets could be used to explain the inconsistency, the results of smoothed downside beta are not intuitively appealing and show that investors dislike assets with low downside risk and require a premium to compensate lower downside losses. It is also inconsistent with the analytical results from Kahneman and Tversky (1979) and Gul (1991) in the utility literature and the survey results from Lee *et al.* (2008a). In fact, these controversial results have highlighted the severity of smoothing bias in direct properties. The smoothing bias is not only dampening the actual downside risk of direct property, it also affects the significance of downside beta. This point is further addressed by Panel B.

Table 5: Regression results of downside betas

Model	I	II	III	IV	V
Panel A: Smoothed Downside Betas					
Constant	0.016 (30.000)***	0.018 (28.949)***	0.013 (23.126)***	0.016 (43.002)***	0.013 (16.932)***
$DB_{i,M}^{(E)}$	-0.005 (-10.540)***				
$DB_{i,R_f}^{(E)}$		-0.008 (-12.147)***			
$DB_{i,Z}^{(E)}$			-0.001 (-3.682)***		
$DB_{i}^{(BL)}$				-0.007 (-15.510)***	
$DB_{i}^{(HR)}$					-0.002 (-2.780)***
Adjusted R^2	0.564	0.633	0.129	0.738	0.084
F-Statistics	111.090***	147.546***	13.554***	240.559***	7.730***
Panel B: Unsmoothed Downside Betas					
Constant	0.005 (3.620)***	0.004 (3.174)***	0.005 (4.035)***	0.005 (5.229)***	0.006 (4.936)***
$DB_{i,M}^{(E)}$	0.003 (2.750)***				
$DB_{i,R_f}^{(E)}$		0.003 (2.684)***			
$DB_{i,Z}^{(E)}$			0.003 (2.753)***		
$DB_{i}^{(BL)}$				0.003 (3.419)***	
$DB_{i}^{(HR)}$					0.002 (2.224)**
Adjusted R^2	0.072	0.112	0.068	0.072	0.044
F-Statistics	7.564***	11.690***	7.205***	7.577***	4.946**

Notes: This table reports the results of cross-sectional regressions for examining the efficiency of downside beta in explaining the cross-sectional variation of direct property returns. Each cross-sectional regression is run for each downside beta measure. The models are estimated: $E(R) = \alpha + \gamma(RV) + \varepsilon$ where $E(R)$ is the average returns of properties, α is the intercept, RV denotes the downside betas (including DB_i^{BL}, DB_i^{HR}, $DB_{i,M}^{E}$, $DB_{i,Rf}^{E}$ and $DB_{i,Z}^{E}$), ε represents the error term. *, **, *** denotes significance at the 10%, 5%, 1% level respectively.

The regression results of Panel B in Table 5 exhibit contradictory results. A positive and statistically significant coefficient on downside beta is documented in Models I-V, illustrating that investors require a positive premium for high downside risk. These support the previous findings on downside betas in the stock and LPT markets in which downside beta is priced and confirms that investors only require a reward for accepting higher downside risk. Importantly, the coefficients on downside betas remain almost unchanged from Models I-IV at 0.003, although little variation is found for Model V.

It is also important to note that the significant discrepancy in results between Panels A and B are attributable to the smoothing bias. Interestingly, these results are consistent with the findings from Geltner (1989) who also found negative betas for US direct properties.

Nonetheless, positive betas are demonstrated once the smoothing bias is adjusted. The conflicting results from smoothed and unsmoothed downside betas clearly show evidence of downside beta is influenced by the smoothing bias. Another important point from Table 5 is that the magnitudes of downside betas are relatively small in all models, suggesting that downside beta itself is unable to fully explain the cross-sectional variations of direct property returns. This supports the finding from Lee *et al.* (2008b). Obviously, additional factors should be introduced into the model[2].

In summary, a positive reward is required for high unsmoothed downside beta, whereas the negative premium that is associated with low smoothed downside beta. These findings also address the importance of correcting the appraisal-smoothing in direct properties and failure to account for the smoothing bias in direct properties will also lead to misleading and sceptical results for the efficiency of downside beta.

Downside betas and property types

To shed more light on the efficiency of downside beta, this section investigates the significance of downside beta in explaining direct properties with controlling the effect of different property types. Equation (5) is controlled by a set of dummy variables to Equation (6) as follows:

$$E(R) = \alpha + \gamma(RV) + \sum_{i=1}^{2} bD_i + \varepsilon \qquad (6)$$

where D_i is a set of dummy variables for 3 types of property. Specially, industrial is specified as (1,0), office is specified as (0,1) and retail is denoted by (0,0).

[2] The focus of this paper is the impact of smoothing on the efficiency of downside beta. Thus, introducing additional factors into the model is beyond the scope of this paper.

Table 6: Regression results of downside betas with controlling for different types of property

Model	I	II	III	IV	V
Panel A: Smoothed Downside Betas					
Constant	0.015 (20.096)***	0.017 (18.140)***	0.012 (21.130)***	0.017 (27.273)***	0.011 (12.007)***
$DB_{i,M}^{(E)}$	-0.004 (-5.793)***				
$DB_{i,R_f}^{(E)}$		-0.006 (-6.815)***			
$DB_{i,Z}^{(E)}$			0.000 (1.259)		
$DB_{i}^{(BL)}$				-0.007 (-10.388)***	
$DB_{i}^{(HR)}$					0.000 (0.198)
D_1	0.000 (0.735)	0.000 (0.241)	0.002 (3.276)***	-0.001 (-2.584)**	0.002 (2.944)***
D_2	-0.002 (-3.926)***	-0.002 (-3.467)***	-0.003 (-4.941)***	-0.002 (-3.550)***	-0.003 (-5.345)***
Adjusted R^2	0.649	0.672	0.497	0.778	0.487
F-Statistics	50.498***	59.172***	28.962***	100.566***	27.921***
Panel B: Unsmoothed Downside Betas					
Constant	0.005 (3.564)***	0.005 (3.300)***	0.005 (3.796)***	0.007 (5.058)***	0.006 (4.892)***
$DB_{i,M}^{(E)}$	0.003 (2.757)***				
$DB_{i,R_f}^{(E)}$		0.003 (2.533)**			
$DB_{i,Z}^{(E)}$			0.003 (2.966)***		
$DB_{i}^{(BL)}$				0.002 (1.437)	
$DB_{i}^{(HR)}$					0.002 (2.533)**
D_1	0.001 (1.353)	0.001 (1.265)	0.001 (1.436)	0.001 (0.891)	0.001 (1.214)
D_2	-0.002 (-2.984)***	-0.002 (-2.955)***	-0.002 (-3.061)***	-0.003 (-2.962)***	-0.002 (-2.483)**
Adjusted R^2	0.254	0.244	0.264	0.205	0.244
F-Statistics	10.654***	10.150***	11.159***	8.306***	10.151***

Notes: This table reports the results of cross-sectional regressions by controlling for different types of property. Each cross-sectional regression is run for each downside beta measure. The models are estimated: $E(R) = \alpha + \gamma(RV) + \sum_{i=1}^{2} bD_i + \varepsilon$

where $E(R)$ is the average returns of properties, α is the intercept, RV denotes the downside betas (including DB_i^{BL}, DB_i^{HR}, $DB_{i,M}^{E}$, $DB_{i,Rf}^{E}$ and $DB_{i,Z}^{E}$), ε represents the error term, D_i is a set of dummy variables for 3 types of property. Specially, industrial is specified as (1,0), office is specified as (0,1) and retail is denoted by (0,0).

*, **, *** denotes significance at the 10%, 5%, 1% level respectively.

Table 6 exhibits the results from Equation (6), accounting for the different types of property. Panel A of Table 6 displays the results of smoothed downside betas and little variation is evident in comparison to Table 5 in which a negative and statistically significant smoothed downside beta is evident in Regressions I, II and IV. However, a positive and insignificant coefficient on downside beta is found in Regressions III and V. In other words, the results are still evident for smoothed downside beta even though property types are controlled.

Panel B of Table 6 presents the results for unsmoothed downside betas. After the additional controls for different types of property are included, strong evidence of a positive premium for downside beta is still observed in which the coefficient on downside beta remains consistently positive at 0.003 with a robust and highly significant t-statistic. However, Model IV shows some variation where the unsmoothed downside beta coefficient is positive, but not statistically significant. In brief, these results have reinforced the baseline results of unsmoothed downside beta and confirmed that a positive premium is required for downside losses.

Interestingly, the coefficient on the dummy variable of office sector (D_2) is negative (-0.002) and statistically significant at least at 5%, suggesting that a negative risk premium is required for this sector and the average return of office sector is lower by around 0.2% than the average returns of retail properties. On the other hand, the coefficients of D_1 from Panels A and B are positive and insignificant in general, indicating that no significant difference is observed between industrial and retail properties.

The negative premium associated with office property can be explained by the poor performance of this sector in which the office sector offered the lowest return, while the highest level of risk in comparison to industrial and retail properties over this study period. This may also reflect investors favouring office assets. A survey of Australian investor sentiment has also confirmed this point (JLL, 2007). Coincidently, Cheng (2005) also found that U.S. office investors also willing to pay a high price for office properties, although the returns of office properties are low. Importantly, the results also suggest that little return enhancement could be obtained by including office properties in a property portfolio. Hence, the optimal levels of office properties in a property portfolio need to be critically assessed; particularly given the clear different performance characteristics.

Overall, the discrepancy results between smoothed and unsmoothed results are observed even after the types of property are controlled. Specifically a positive reward for high unsmoothed downside betas is still evident and a problematic negative premium is also manifested for smoothed downside betas. Furthermore, sectoral differences are also demonstrated in which office properties are underperformed in comparison to other sectors. This indicates that property investors should recognise the differences in formulating their asset allocations.

Robustness check

An investigation of different smoothing parameters is also performed since the baseline results could be somewhat sensitive to the unsmoothing model. Another 2 parameters (0.167 and 0.25) are selected[3]. The results are stipulated in Table 7.

Table 7: Regression results of downside betas with different smoothing parameters

Model	I	II	III	IV	V
Panel A: Smoothing Parameter of 0.17					
Constant	0.008 (5.937)***	0.008 (5.676)***	0.009 (6.625)***	0.009 (8.017)***	0.009 (8.078)***
$DB_{i,M}^{(E)}$	0.003 (2.413)**				
$DB_{i,R_f}^{(E)}$		0.003 (2.418)**			
$DB_{i,Z}^{(E)}$			0.003 (2.401)**		
$DB_{i}^{(BL)}$				0.003 (3.020)***	
$DB_{i}^{(HR)}$					0.002 (1.950)*
Adjusted R^2	0.054	0.054	0.053	0.087	0.032
F-Statistics	5.821**	5.846**	5.763**	9.123***	3.801*
Panel B: Smoothing Parameter of 0.25					
Constant	0.010 (8.265)***	0.010 (7.905)***	0.011 (9.854)***	0.010 (10.756)***	0.011 (10.657)***
$DB_{i,M}^{(E)}$	0.002 (2.082)**				
$DB_{i,R_f}^{(E)}$		0.002 (2.110)**			
$DB_{i,Z}^{(E)}$			0.002 (1.829)*		
$DB_{i}^{(BL)}$				0.003 (3.488)***	
$DB_{i}^{(HR)}$					0.002 (1.960)*
Adjusted R^2	0.038	0.039	0.027	0.116	0.032
F-Statistics	4.337**	4.451**	3.347**	12.165***	3.840*

Notes: This table reports the results of cross-sectional regressions with different smoothing parameters for examining the robustness for the efficiency of unsmoothed downside betas. Each cross-sectional regression is run for each downside beta measure. The models are estimated:

$E(R) = \alpha + \gamma(RV) + \varepsilon$ where $E(R)$ is the average returns of properties, α is the intercept, RV denotes the downside betas (including DB_i^{BL}, DB_i^{HR}, $DB_{i,M}^{E}$, $DB_{i,Rf}^{E}$ and $DB_{i,Z}^{E}$), ε represents the error term.

*, **, *** denotes significance at the 10%, 5%, 1% level respectively.

[3] The rationales of selecting both parameters are based on the assumption that new information will be incorporated with the average lag of 3 quarters and 5 quarters respectively.

Interestingly, the efficiency of unsmoothed downside betas remains unchanged to different smoothing parameters. Specifically, all regressions either with a 0.167 or 0.25 smoothing parameter show a fairly consistent positive coefficient on unsmoothed downside beta in Panels A and B. Even though a higher smoothing parameter (0.25) reduces the magnitude of coefficients on unsmoothed downside betas from 0.003 to 0.002, the coefficients remain positive and statistically significant at least at 10%. These results have reinforced the baseline results in which compensation is required by investors for bearing higher downside risk. Additionally, the Estrada downside beta definition especially $DB_{i,M}^{(E)}$ appears as a preferred downside beta estimation procedure in which its significance is less sensitive to different smoothing parameters and different types of properties.

In summary, the baseline results of corrected downside betas are robust to different smoothing parameters. In other words, the finding of a reward is required by direct property investors for higher downside risk is robust.

PROPERTY INVESTMENT IMPLICATIONS AND CONCLUSIONS

There is a growing body of literature supporting the use of downside beta in asset pricing. However, little study has been placed to examine the efficiency of downside beta in explaining the cross-sectional variations of direct property returns with addressing the smoothing issue. This study aims to address this gap by examining the impact of smoothing on the efficiency of downside beta in asset pricing.

There are several important findings from this study. Firstly, smoothed and unsmoothed downside betas are statistically distinguishable. More specifically, the downside beta of direct property is underestimated if the appraisal-smoothing bias is failed to be adjusted. Secondly, a positive and statistically significant downside premium is evident for unsmoothed downside betas, whereas a sceptical negative premium is found for smoothed downside betas. This further highlights that the smoothing bias does appear to be a serious issue in downside beta estimation, and should be treated with caution. Thirdly, the results of smoothed and unsmoothed downside betas are robust even if the property types are controlled. Similar robust findings of corrected downside beta are also found for different smoothing parameters. Interestingly, sectoral differences are also evident in which a negative premium is associated with office properties.

These findings have provided further insight into the pricing of direct properties with several important practical implications. Importantly, property analysts and investors should consider the employment of downside beta in their asset pricings with respect to it as an efficient risk measure, although de-smoothing efforts should be placed for valuation-based property returns. More importantly, the sceptical results of smoothed downside beta has highlighted that the valuation-based direct property returns should be adjusted and corrected in which the smoothing bias would affect the efficiency of downside beta. The finding of sectoral differences also highlights the importance of understanding these differences in developing a property investment strategy. Overall, these findings have provided invaluable insights into the impact of smoothing on downside beta and offered an improved understanding for investors in direct property investment.

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