Downside Beta and Appraisal Based Real Estate 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. The results are robust after controlling for the different property types and different smoothing parameters. These findings provide further insights into the pricing of appraisal based real estate indices.

Keywords: Direct Property, Downside Beta, Smoothing, Australia

1.0 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 sectors 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.

Although 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

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

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 dissimilar with financial assets, direct property returns are appraisal based returns and the values are not derived from market transactions. This issue is commonly referred as smoothing bias in the real estate literature. Numerous real estate studies have also demonstrated that the smoothing bias is presence in many appraisal based real estate indices and its consequences are severe (Geltner et al., 2003, a review). 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 appraisal based real estate returns. Second, this would probably 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 appraisal based real estate returns.

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

2.0 LITERATURE REVIEW

Lower Partial Moment-CAPM (LPM-CAPM) has become increasingly accepted in respect to the weak empirical support for the CAPM (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, Nawrocki, 1999). 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 required 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 concern 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 have demonstrated the efficiency of downside beta in stock and REIT asset pricings, there is little work 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 appraisal 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 performances of real estate could be caused by the smoothing bias. Importantly, the smoothing in appraisal based returns has also engendered the underestimation of actual risk (Geltner, 1993, Giliberto, 1993, Newell and MacFarlane, 1995). Lai and Wang (1998), on the other hand, found contradict results where an overestimation of risk in appraisal based real estate return is presented. More recently, Edelstein and Quan (2006) compared appraised 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) and Giliberto (1993) also demonstrated the impacts 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) have offered empirical evidence of divergence beta results from uncorrected and corrected smoothing bias 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, no study has been placed on the impact of smoothing on the efficiency of downside beta in an appraisal based real estate return series.

3.0 DATA AND METHODOLOGIES

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. Consistent with Newell and Peng (2007), this study commenced from Q3:1995 with regard to no quarterly data is available prior to 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 based on 87 sub-sectors are reported in Table 1. The descriptive statistics of these 87 IPD/ PCA property indices are exhibited in Appendix I.

(Insert Table 1)

As depicted in Table 1, the average return of these sub-sectors is almost 3% per quarter with the average standard deviation of 1.55%. The skewness statistic also shows that these return distributions are positively skewed, suggesting that the downside variability of these sub-sectors is higher than the upside. It also indicates that the return distributions of direct properties are asymmetrically distributed. In addition, a strong excess kurtosis is also observed from Table 1. 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.

Methodology

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

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

where W is the smoothing parameter, R_t^* is the current appraisal-based return, R_{t-1}^* is the previous appraisal-based return and R_t is the contemporaneous transaction-based return. In this study, the smoothing parameter of 0.2 was selected[2]. 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. Recently, Galagedera (2007) highlighted the importance of choosing an appropriate downside beta definition.

[2] The 0.2 parameter was chosen in response to Geltner et al. (2007) suggested that $W = 1/(\overline{L}+1)$ and $\overline{L}$ is the average number of lag.

Thus, in this study, three common measures of downside beta that are proposed in the literature are employed. These definitions are:

Bawa and Linderberg (1977) downside beta definition is the first measure that is employed in this study. The downside beta $\left(DB_i^{BL}\right)$ 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 $\left(DB_i^{E}\right)$ as follows:

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

where B_i and B_m are the benchmark for asset i and market respectively. Estrada (2006) suggested that three different cutoff points (mean, risk-free rate and zero return) can be applied to this measure. As such, these benchmarks: (1) mean return ($DB_{i,M}^{(E)}$), (2) risk-free rate ($DB_{i,Rf}^{(E)}$) and zero target rate ($DB_{i,Z}^{(E)}$) are utilised in this study.

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:

$$E(R) = \alpha + \gamma(RV) + \varepsilon \quad (5)$$

$E(R)$ 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. Similar procedure is also employed by Estrada (2002) and Cheng (2005).

4.0 RESULTS AND DISCUSSIONS

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 only appears to be a more efficient risk measure if return distributions are skewed and in asymmetrical form. The results are reported in Table 2.

(Insert Table 2)

A number of points are nothing from Table 2. Firstly, consistent with the preliminary results, there is no evidence to support these return distributions is normally distributed. Almost 86% of the sample can be 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 few sectors that emerge normal distribution. Possible explanation is these sub 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, 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, the Shapiro-Wilk test appears as the more 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 than the mean of $DB_{i}^{(BL)}$.

(Insert Table 3)

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 quite comparable results of downside beta estimations. Specifically, the averages of these definitions are around 1.1. Similar results are also obtained from 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; in general, emerge much larger in magnitude than smoothed downside betas, excepting $DB_{i,Z}^{(E)}$. The smoothing bias in the appraisal 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.

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

(Insert Table 4)

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 appraisal 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 z-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 is also reasonable to hypothesise that the smoothing bias in appraisal based real estate indices would 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 the Equation (5) of 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 for 5 different definitions of downside beta.

(Insert Table 5)

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 at al., 2008b). Although different markets could be used to explain the inconsistency, the results 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 contrast, the regression results of Panel B in Table 5 exhibit contradictory results. A positive and statistically significance 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 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[3].

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

[3] 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.

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

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

(Insert Table 6)

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 doubtful 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 little variation where the unsmoothed downside beta 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 dummy variable of office sector is negative and statistically significant at least at 5%, suggesting that a negative risk premium is required for this sector. It 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 the industrial and retail sectors over this study period.

Overall, the discrepancy results between smoothed and unsmoothed results are observed even the types of property are controlled in which a positive reward for high unsmoothed downside betas is still evident and a problematic negative premium is also manifested for smoothed downside betas.

Robustness Check

An investigation of different smoothing parameters is also performed in order to reinforce the baseline results. Another 2 parameters (0.167 and 0.25) are selected. The rationales of selecting both parameters are based on the assumption that new information will be incorporated with an average lag of 3 quarters and 5 quarters respectively. The results are stipulated in Table 7.

(Insert Table 7)

Interestingly, the efficiency of unsmoothed downside betas remains unchanged to different smoothing parameters. Specifically, all regressions either with 0.167 or 0.25 smoothing parameter show a fairly consistent positive coefficient on unsmoothed downside beta in Panels A and B. Even though higher smoothing parameter (0.25) reduces the magnitudes of coefficients on unsmoothed downside betas from 0.003 to 0.002, the coefficients remain positive and statistically significant at least at 10%. In summary, the baseline results of corrected downside betas are robust to different smoothing parameters.

5.0 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 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 smoothing does appear to be a serious issue in downside beta estimation, and should be treated with caution. Thirdly, there is no evidence of controlling different types of property into the model is essential in which both smoothed and unsmoothed downside betas are robust even the property types are controlled. Similar robust finding is also found for different smoothing parameters.

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 is an efficient risk measure, although de-smoothing efforts should be placed for appraised based real estate returns. More importantly, this is a much more appropriate to adjust the appraisal based direct property returns in which the smoothing bias would affect the efficiency of downside beta. 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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Table 1: Summary Statistics of Direct Property Quarterly Returns: Q3:1995-Q2:2008

Statistics	**Direct Property Sub-Sectors**
Mean	3.038%
Median	2.665%
Maximum	21.014%
Minimum	-9.759%
Count	87
Standard Deviation	1.551%
Skewness	1.218
Kurtosis	5.813

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%

*These figures are the percentage of direct property sub-sectors in the sample that are rejected by normality tests.

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
Minimum	0.277	0.397	0.000	-0.287	0.162
Maximum	2.445	1.961	4.987	1.790	1.976
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
Minimum	0.451	0.475	0.444	0.107	-0.115
Maximum	1.917	1.824	2.019	1.745	1.885
Count	86	86	86	86	86

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: * denotes significance at the 10% level; ** represents significance at the 5% level and *** denotes significance at the 1% level.

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)***
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)**

Notes: * denotes significance at the 10% level; ** represents significance at the 5% level and *** denotes significance at the 1% level.

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)
Dummy Industrial	0.000 (0.735)	0.000 (0.241)	0.002 (3.276)***	-0.001 (-2.584)**	0.002 (2.944)***
Dummy Office	-0.002 (-3.926)***	-0.002 (-3.467)***	-0.003 (-4.941)***	-0.002 (-3.550)***	-0.003 (-5.345)***
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)**
Dummy Industrial	0.001 (1.353)	0.001 (1.265)	0.001 (1.436)	0.001 (0.891)	0.001 (1.214)
Dummy Office	-0.002 (-2.984)***	-0.002 (-2.955)***	-0.002 (-3.061)***	-0.003 (-2.962)***	-0.002 (-2.483)**

Notes: * denotes significance at the 10% level; ** represents significance at the 5% level and *** denotes significance at the 1% level.

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)*
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)*

Notes: * denotes significance at the 10% level; ** represents significance at the 5% level and *** denotes significance at the 1% level.

Appendix I: Summary Statistics of 87 Sub-sector Quarterly Returns: Q3:1995-Q2:2008

Sectors	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
Composite Property	2.851%	2.539%	5.755%	1.376%	0.983%	52
Retails	3.006%	2.633%	6.796%	1.663%	1.191%	52
Offices	2.632%	2.300%	7.092%	0.675%	1.228%	52
Industrials	3.307%	3.184%	6.907%	1.863%	0.912%	52
Australian Non CBD Office	3.067%	2.754%	8.452%	1.134%	1.255%	52
Australian CBD Office	2.550%	2.177%	7.118%	0.343%	1.317%	52
Australian CBD Office Premium	2.695%	2.305%	8.973%	0.700%	1.560%	52
Australian CBD Office Grade A	2.409%	2.164%	6.434%	-0.844%	1.278%	52
Australian CBD Office Grade B	2.672%	2.334%	7.663%	-0.617%	1.632%	52
Australian CBD Office Grade C and D	3.209%	2.716%	18.511%	-2.253%	3.278%	52
Australian CBD Office Premium & A	2.513%	2.128%	7.227%	0.629%	1.289%	52
Australian CBD Office: Secondary Grade	2.720%	2.366%	7.580%	-0.902%	1.650%	52
Australian CBD Office: NLA less than 7,500	2.289%	2.297%	8.337%	-3.100%	2.066%	52
Australian CBD Office: NLA between 7,500 and 15,000	2.675%	2.461%	12.140%	0.000%	1.944%	52
Australian CBD Office: NLA between 15,000 and 30,000	2.661%	2.268%	7.166%	0.253%	1.267%	52
Australian CBD Office: NLA greater than 30,000	2.528%	2.135%	7.630%	0.505%	1.396%	52
Sydney CBD Office	2.380%	2.027%	6.293%	-0.856%	1.294%	52
Melbourne CBD Office	2.603%	2.296%	6.286%	0.772%	1.211%	52
Brisbane CBD Office	2.925%	2.035%	15.112%	-1.158%	2.799%	52
Perth CBD Office	3.531%	2.530%	14.046%	0.638%	2.922%	52
Adelaide CBD Office	2.218%	2.357%	8.418%	-3.514%	2.184%	52
Canberra Region Office	2.228%	2.730%	6.596%	-7.885%	2.914%	52
Sydney Non CBD Office	3.057%	2.838%	9.649%	-0.049%	1.472%	52
Melbourne Non CBD Office	2.863%	2.645%	6.990%	0.803%	1.173%	52
Brisbane Non CBD Office	3.169%	2.229%	21.014%	-0.786%	3.634%	52
Sydney CBD Office: Grade A	2.084%	1.858%	6.794%	-1.320%	1.323%	52
Sydney CBD Office: Grade B, C and D	2.676%	2.455%	7.331%	-0.375%	1.649%	52
Lower North Shore Office	2.948%	2.778%	10.594%	-1.325%	1.738%	52
North Ryde and Paramatta Office	2.969%	2.754%	8.689%	0.977%	1.355%	52
Rest of Sydney Non-CBD office	2.914%	2.552%	7.247%	-0.106%	1.427%	52

Australian Super and Major Regional Retail	2.996%	2.665%	6.921%	1.159%	1.307%	52
Australian Regional Retail	2.844%	2.575%	6.646%	0.603%	1.330%	52
Australian Sub Regional Retail	3.223%	2.764%	7.194%	1.475%	1.443%	52
Australian Neighbourhood Retail	3.618%	3.103%	7.305%	1.281%	1.689%	52
Australian Other Retail	2.791%	2.410%	6.951%	-2.486%	1.523%	52
Australian Retail: Metropolitan Centres	3.013%	2.596%	7.083%	1.556%	1.357%	52
Australian Retail: Country Centres	3.097%	2.597%	7.437%	1.116%	1.451%	52
Australian Retail: NLA Less than 30,000	3.254%	2.889%	6.396%	1.341%	1.140%	52
Australian Retail: NLA between 30,000 and 50,000	2.975%	2.400%	8.779%	1.529%	1.645%	52
Australian Retail: NLA greater than 50,000	2.942%	2.672%	6.754%	0.841%	1.250%	52
New South Wales Retail	3.031%	2.812%	5.801%	1.442%	1.138%	52
Queensland Retail	3.006%	2.608%	8.139%	0.585%	1.413%	52
Victorian Retail	2.973%	2.206%	8.375%	0.450%	1.728%	52
Western Australian Retail	3.146%	2.375%	9.333%	0.801%	1.879%	52
South Australian Retail	2.917%	2.340%	9.458%	1.246%	1.452%	52
New South Wales Retail: Major, Super Regional and Regional	2.961%	2.632%	7.709%	1.371%	1.288%	52
New South Wales Retail: Sub Regional Centres	3.559%	3.342%	7.500%	0.352%	1.578%	52
New South Wales Retail: Other	2.861%	2.681%	9.678%	-1.913%	1.777%	52
Victorian Retail: Major, Super Regional and Regional	2.883%	2.003%	9.604%	0.343%	1.959%	52
Victorian Retail: Sub Regional Centres	2.991%	2.485%	8.681%	-0.708%	1.810%	52
Queensland Retail: Major, Super Regional and Regional	3.092%	2.661%	6.922%	-0.224%	1.438%	52
Queensland Retail: Sub Regional Centres	2.947%	2.527%	8.078%	-0.426%	1.719%	52
Queensland Retail: Other	3.275%	2.396%	9.539%	-2.013%	2.277%	52
Australian Industrial: High Tech	3.179%	3.030%	6.640%	1.807%	0.931%	52
Australian Industrial: Unit Estate	3.552%	3.208%	11.204%	1.748%	1.687%	52
Australian Industrial: Warehouse	3.342%	2.941%	6.206%	0.474%	1.181%	52
Australian Industrial: NLA less than 7,000	3.412%	2.889%	8.026%	1.353%	1.491%	52
Australian Industrial: NLA between 7,000 and 12,000	3.327%	3.138%	6.573%	1.762%	1.012%	52
Australian Industrial: NLA between 12,000 and 25,000	3.243%	3.131%	6.682%	1.654%	0.997%	52
Australian Industrial: NLA greater than 25,000	3.342%	3.217%	7.348%	1.785%	1.062%	52
Australian Industrial: Value less than $6m	3.119%	2.726%	9.027%	-0.187%	1.598%	52
Australian Industrial: Value between $6m and $11m	3.194%	2.885%	6.138%	1.405%	0.917%	52

Australian Industrial: Value between $11m and $20m	3.414%	3.161%	7.790%	1.853%	1.110%	52
Australian Industrial: Value greater than $20m	3.319%	3.208%	6.836%	1.840%	1.033%	52
Australian Industrial: Warehouse secondary	3.326%	2.888%	9.480%	-3.701%	1.823%	52
Sydney Industrial	3.323%	3.182%	7.284%	1.793%	1.028%	52
Melbourne Industrial	3.181%	2.727%	6.699%	-0.509%	1.386%	52
Brisbane Industrial	3.412%	2.521%	8.904%	1.209%	1.932%	52
Sydney Industrial: Central West	3.201%	2.875%	7.587%	1.345%	1.386%	52
Sydney Industrial: North	3.211%	2.946%	6.878%	1.698%	1.026%	52
Sydney Industrial: Outer West	3.175%	2.890%	6.720%	1.462%	1.164%	52
Sydney Industrial: South	3.881%	3.342%	10.211%	1.675%	1.923%	52
Sydney Industrial: NLA Less than 7,000	3.611%	3.159%	11.056%	0.481%	1.958%	52
Sydney Industrial: NLA between 7,000 and 12,000	3.435%	3.125%	6.463%	2.029%	1.086%	52
Sydney Industrial: NLA between 12,000 and 25,000	3.202%	3.198%	7.332%	1.499%	1.096%	52
Sydney Industrial: NLA greater than 25,000	3.357%	3.241%	8.013%	1.751%	1.311%	52
Sydney Industrial: Value less than $10m	3.303%	2.984%	7.977%	-0.966%	1.463%	52
Sydney Industrial: Value between $10m and $20m	3.525%	3.287%	8.191%	1.959%	1.213%	52
Sydney Industrial: Value greater than $20m	3.265%	3.191%	7.492%	1.667%	1.195%	52
Rest Of Australia Non CBD Office	3.106%	2.432%	8.695%	0.804%	1.697%	38
Sydney CBD Office: Grade Premium	2.665%	2.001%	8.674%	0.345%	1.814%	32
Australian Bulky Goods Retail	3.013%	2.648%	8.527%	0.290%	1.565%	35
Rest of Australia Retail	3.476%	3.246%	7.435%	0.012%	1.585%	32
Victorian Retail: Other	2.793%	2.568%	7.237%	-9.759%	2.359%	42
Australian Industrial: Distribution	2.947%	2.693%	6.825%	-2.529%	1.380%	48
Australian Industrial: Warehouse prime	3.367%	2.919%	7.885%	1.600%	1.327%	44
Rest of Australia Industrial	3.359%	2.705%	11.269%	-2.134%	2.276%	48

Source: IPD/PCA (2008)