RISK MEASUREMENT AND LISTED PROPERTY TRUST INVESTMENT STRATEGIES : FOCUSING ON THE DOWNSIDE

VINCENT PENG
University of Western Sydney

ABSTRACT

Measuring investment risk precisely is critical to investment strategies. In common practice, the most popular measure of risk is standard deviation. However, standard deviation makes no distinction between positive and negative deviations from the mean. Such risk measurement could lead to biased decision making, given that asset returns are generally not symmetrically distributed.

In this paper, risk is confined to adverse outcomes that are measured by the negative semi-deviation. By examining Australian Listed Property Trusts (LPTs) for the period of 1985- 2004, this paper illustrates how the differentiation between risk (semi-deviation) and uncertainty (standard deviation) make significant differences in performance measurement and optimal portfolio construction. This paper demonstrates that the concept and application of downside risk is a valuable construct to LPT investment strategies.

Keywords: Listed property trusts, investment strategies, investment risk, downside risk

INTRODUCTION

The ability of accurately assessing asset performance and adding outperforming assets into a portfolio drives the success of portfolio management, because the superiority of a portfolio is largely underpinned by how well the portfolio is constructed, which is especially true when liquidity is taken into account (Peng, 2004).

Asset performance may be explained by 'luck' and 'risk'. Good performance might come by luck. To do the right thing for the wrong reason is not uncommon in the investment world, neither is it uncommon that an asset proves to perform well for reasons unrelated to its manager's initiatives. Since 'luck' ought not to have a persistent effect, the influence of luck can be relatively easily eliminated by selecting a sample large enough to allow the effects of 'good luck' and 'bad luck' cancel each other.

Good performance may also simply result from the high level of risk undertaken. Raw return is not an adequate measure of performance. To compare like with like, the level of risk needs to be taken into account when assessing asset performance. In fact, portfolio construction and buy/sell decisions are mostly based on, along with other considerations such as strategic alliances, the risk-adjusted performance of assets.

In assessing risk-adjusted performance, standard deviation has been commonly used as the proxy for risk. However, as a statistic, standard deviation weights equally a scenario with returns rising above average and a scenario with returns falling below average, and makes no distinction between positive and negative deviations from the mean. Therefore, it simply measures volatility and uncertainty. This measurement of risk has serious drawbacks and may lead to biased decisions.

Investors are risk adverse and so expect to be adequately compensated for holding risky assets. More often than not, investors are less concerned about assets generating returns above expectations. To investors, what is called ‘risk’ are any outcomes that fall short of objectives, which are the downside risk and measured by the negative semi-deviation.

There have been arguments that standard deviation and downside semi-deviation would generate very similar results, if not the same, in assessing asset performance and constructing the optimal portfolios. For example, Sharpe (1998) analysed average monthly standard deviations of excess returns and also the downside risk in a sample of 1286 funds over a three-year period. His findings show a close correlation between the two measures, with a correlation coefficient of 0.93. In a stable market, where asset returns generally follow a symmetric distribution, these arguments might have a stand. This is because if asset returns are symmetrically distributed, downside semi-deviation and standard deviation will be perfectly correlated with a correlation of one, in which case, the results based on semi-deviation would simply duplicate those based on standard deviation.

However, there has been extensive evidence suggesting that asset returns are not always symmetrically distributed; for example, Kritzman (1994), Alles and Kling (1994), DeFusco et al (1996), Chunhachinda et al (1997) and Bekaert et al (1998), etc. In the case that the distribution of asset returns is skewed, standard deviation will result in over- or under-estimation of true risk, which in turn leads to poor decision making. In such cases, semi-deviation, measuring the negative deviation from mean returns or a certain target return (TR) should prove much precise measurement of risk.

This study examines Australian Listed Property Trusts (LPTs). It demonstrates how downside semi-deviation will generate distinct results and lead to distinct conclusions in assessing risk-adjusted performance and constructing optimal portfolios compared to standard deviation, highlighting the significance of focusing on the downside to the formation of LPTs investment strategies. Being the first study employing downside risk concept in the context of LPT investment strategies, it complements research literature in the field of LPT studies and provides significant implications for LPT investment strategies.

The significant practical implications for LPT portfolio managers highlighted in this study shall also prove a useful reference to portfolio managers and academia who cover European and Asian markets where Real Estate Investment Trusts (REITs) are emerging, with assets having a greater tendency towards risk of downside in the emerging markets (Raj, *et al*, 2003 and Bekaert, *et al*, 1998).

The remainder of this paper is structured as follows. Section two reviews the literature on downside risk. Section three describes the data and then introduces the methodology used in this study. Section four provides results and analysis. Practical implications are illustrated and discussed in section five, and the last section provides concluding comments.

LITERATURE REVIEW

The concept of downside risk is not new. Roy (1952) addresses the concern of the downside deviation in the form of a 'safety first' rule that measures the outcomes falling below a target return. Mao (1970) reports survey results suggesting that executive risk perceptions are dominated by the concern of undesirable or adverse outcomes.

Hoskins (1973) considers three mathematical proxies for downside risk: probability of loss, the expected value of loss and the semi-variance. The probability of loss is redeemed to be unsatisfactory because it fails to take any account of the quantum of possible losses. The expected value of loss, a measure employed by Domar and Musgrave (1944), is also deemed to be unsatisfactory because a utility function based on the expected return and expected value of loss, as shown as Markowitz (1959), is linear in the range of negative outcomes. The semi-variance was suggested to be the appropriate measurement for downside risk.

The concept of downside risk has since been well documented in the finance literature; for example, Hogan and Warren (1974), Porter (1974), Fishburn (1977), Levy and Markowitz (1979), Scott and Horvath (1980), Harlow (1991) and Nawrocki (1991).

Sivitanides (1998) and Sing and Ong (2000) introduce the concept of downside risk to the field of real estate. Sivitanides (1998) and Sing and Ong (2000) take similar approaches to address the question of which of the procedures, traditional mean-variance analysis or semi-variance downside risk analysis, produces less risky portfolios at a given expected return. However, as Cheng and Wolverton (2001) point out, the comparisons made by Sivitanides (1998) and Sing and Ong (2000) are logically flawed, because the two procedures use different risk measurement, ie, variance for mean-variance portfolios and semi-variance for downside risk analysis.

Using a bootstrap procedure to generate simulated pseudo ex ante data sets, Cheng (2001) takes an alternative approach to assess the superiority of mean-variance optimal portfolio and semi-variance portfolio by comparing the terminal wealth produced by different portfolios. The results from Cheng (2001) suggest that ex ante semi-variance portfolio return distributions tend to exhibit smaller left tails and larger median returns than those of mean-variance portfolios. In the practical sense, ex ante semi-variance procedure is superior, not only because it produces portfolios that are more desirable to risk adverse investors who welcome every bit of downside risk reduction, it also appears to improve portfolio performance with higher median returns, although statistical significance of such improvement requires further testing.

In the real estate field, the concept of downside risk has also been used by Sing and Ling (2003) to examine the role of Singapore property trusts in a downside risk asset allocation framework. Based on the historical relationship between the returns of stocks, bonds and Australian LPTs, Sing and Ling (2003) simulates ex-post returns for Hypothetical Property Trusts (HPTs) in Singapore for the period of March 1995 to March 2002. Under the framework of downside risk, Sing and Ling (2003) demonstrate that the HPTs outperformed local stocks and bonds, sector-specific HPTs provide greater diversification benefits than diversified HPTs, and HPTs are to take up a major proportion of optimized portfolios when the expected rate of portfolio return increase.

In the literature search, no previous studies have been found that employ the concept of downside risk to examine the performance of Australian LPTs and relevant investment strategy issues. This study employs semi-deviation, the square root of semi-variance, to measure risk. It demonstrates the significance of differentiating risk as measured by downside semi-deviation from uncertainty or volatility as measured by standard deviation in the process of assessing LPT performance and constructing optimal portfolios, providing significant implications for LPT investment strategies.

DATA AND METHODOLOGY

Data

Two portfolios are examined in this study. The first portfolio (Portfolio A) consists of LPTs, Direct Properties and Common Stocks. The second portfolio (Portfolio B) is a pure LPTs portfolio consisting of Commercial LPTs, Retail LPTs and Industrial LPTs. The Property Council of Australia (PCA) Composite Index is used to represent the performance of Direct Properties. The Australian Stock Exchange (ASX) Accumulation Indices of All Ordinaries, LPT 300, Commercial 300, Retail 300 and Industrial 300 are used to represent the performance of Common Stocks, LPTs, Commercial LPTs, Retail LPTs and Industrial LPTs respectively.

Annual returns are compiled from above indices and used in this study. For Portfolio A, annual returns are compiled at a quarterly interval, with PCA data only available at the quarterly basis. For Portfolio B, annual returns are compiled at a monthly interval. The use of annual data in real estate investment research is preferable because it avoids inconsistencies, lags and seasonal problems that are present in quarterly data (Giliberto, 1990; Wheaton and Torto, 1989). Graff (1998) indicates that annual appraisal based returns are appropriate input for calculation of sample correlations aimed to be used in asset allocation models while quarterly returns are not because of seasonal biases. Graff (1998) also indicates that the possibility of correcting such seasonal biases is remote.

Subject to the availability of relevant data series (PCA indices start from December 1984 and Industrial 300 start from July 1993), this study examines Portfolio A for the period of December 1985 to June 2004 (inclusive), and Portfolio B for the period of July 1994 to October 2004 (inclusive).

Methodology

As discussed in the Introduction section, whether downside semi-deviation will make a difference from standard deviation lies in whether asset returns are symmetrically distributed. If asset returns are symmetrically distributed, semi-deviation and standard deviation should produce the same results.

It is therefore important to first study the return distributions of the assets under examination. This study uses skewness to inspect return distributions and calculates downside semi-deviation by means of Lower Partial Moments (LPM).

Return distribution and skewness

Skewness measures asymmetry of the distribution of a series around its mean. Skewness is computed as:

$$S = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{y_i - \bar{y}}{\hat{\sigma}}\right)^3 \qquad (1)$$

where N is the number of observations in the current sample, $\bar{y}$ is the mean of the series and $\hat{\sigma}$ is an estimator for the standard deviation. The skewness of a symmetric distribution, such as the normal distribution, is zero. Positive skewness means that the distribution has a long right tail and negative skewness implies that the distribution has a long left tail.

Downside semi-deviation and lower partial moments

Downside risk can be measured by Lower Partial Moments (LPM) as defined by Fishburn (1977):

$$LPM_n = \int_{-\infty}^{T} (T - R)^n \, df(R) \qquad (2)$$

where T is target return, R_i is the return of asset i, $df(R_i)$ is the probability density function of return on asset i and n is the order of moment that characterises an investor's preference of return dispersion below the target return.

Similarly, Co-Lower Partial Moments (CLPM) is defined by Bawa and Lindenberg (1977) as:

$$\text{CLPM}_n = \int_{-\infty}^{T} (T - R_i)^{n-1} (T - R_j) df(R_i, R_j) \qquad (3)$$

where R_i and R_j are the return of assets *i* and *j*.

For empirical (discrete) distributions, the above definitions take the following computational format:

$$\text{LPM}_n = \frac{1}{m-1} \sum_{t=1}^{m} [Max(0, T - R_{it})]^n \qquad (4)$$

$$\text{CLPM}_n = \frac{1}{m-1} \sum_{t=1}^{m} [Max(0, T - R_{it})]^{n-1} (T - R_{jt}) \qquad (5)$$

where R_{it} represents the return of asset *i* at time t and m is the total number of time periods. The *Max*( ) operator selects the larger of T-R_{it} and zero for calculation. That is, the models only concern asset returns that fall below the investor's target return.

The common classes of LPM are the probability of loss if n=0; the target shortfall if n=1; the target semi-variance if n=2; and the target skewness if n=3. Differences in the way investors perceive risk are captured by n, and an investor's risk aversion increases as n increases. Following Hoskins (1973), this study considers the case of downside risk as being measured by semi-variance (n=2), which is consistent with recent downside risk studies including Sivitanides (1998), Sing and Ong (2000), Cheng (2001) and Sing and Ling (2003), etc. Semi-deviation, which is the square root of semi-variance, is used in this study as a measure of downside risk.

In terms of optimal portfolio construction, a downside risk model essentially uses the same algorithms of the traditional Markowitz's mean variance optimisation model. The difference is the downside risk model minimises semi-variances and co-semi-variances as defined in equations (4) and (5) while mean variance model minimises variances and co-variances.

This study set the first target return (TR1) at 0%, hypothesising that investors are mainly concerned with preserving capital and avoiding losses. The second target return (TR2) is set at 8%, which is ten-year bond yield plus a risk premium, suggesting an investor requires his investments to yield not only the risk free rate but also a premium to compensate the risk he is taking to invest into the relevant assets in the study.

RESULTS AND ANALYSIS

Asset return distributions

Table 1 shows the return distributions of assets in Portfolio A and Portfolio B.

Table 1: Asset return distributions

	Portfolio A		
	LPTs	Direct Properties	Common Stocks
	(December 1985 - June 2004)		
Mean	0.12887	0.10427	0.13646
Median	0.12451	0.10277	0.12787
Standard Deviation	0.10166	0.09355	0.17229
Kurtosis	0.99995	0.87960	0.27517
Skewness	0.63148	0.16194	0.71196
Count	38	38	38
	Portfolio B		
	Commercial LPTs	Retail LPTs	Industrial LPTs
	(July 1994 - October 2004)		
Mean	0.09845	0.12756	0.13775
Median	0.08639	0.12094	0.14114
Standard Deviation	0.06512	0.11843	0.08986
Kurtosis	-0.55113	-0.02233	-0.21277
Skewness	0.27127	0.17870	0.23332
Count	124	124	124

As shown in Table 1, the return distributions of all the assets under examination are positively skewed with a long right tail. The degree of skewness varies across different assets. For example, in Portfolio A, Common Stock returns are the most positively skewed and Direct Property returns are the least positively skewed. In Portfolio B, Commercial LPT returns are most positively skewed and Retail LPTs returns are the least positively skewed. The asymmetric distributions of asset returns are a similar finding to Myer and Webb (1994).

This study also provides evidence that asset return distributions are not stable and may change substantially over time. Table 2 shows the return distributions of the assets in Portfolio A for the evenly divided two sub-periods: December 1985 – December 1994 and June 1995 – June 2004.

Table 2: Asset return distributions

	Portfolio A (December 1985 - December 1994)		
	LPTs	Direct Properties	Common Stocks
Mean	0.13206	0.10831	0.16731
Median	0.09808	0.12538	0.13346
Standard Deviation	0.12710	0.13349	0.22520
Kurtosis	0.05311	-1.14679	-1.14252
Skewness	0.70223	0.02098	0.33866
Count	19	19	19

	Portfolio A (June 1995 - June 2004)		
	LPTs	Direct Properties	Common Stocks
Mean	0.12568	0.10023	0.10561
Median	0.12737	0.10269	0.12228
Standard Deviation	0.07118	0.01169	0.09106
Kurtosis	1.78307	-0.28120	-0.22153
Skewness	-0.32355	-0.52922	-0.43861
Count	19	19	19

As shown in Table 2, returns of LPTs, Direct Property and Common Stocks are all positively skewed (higher downside risks) for the first period but are all negatively skewed (lower downside risks) over the second period. The results are within expectations. While the second period could be characterised as a ‘bull’ market with strong economic fundamentals where downside risks are lower, the first period was dominated by unfavourable market conditions (such as property downturn, high inflation) where downside risks were higher.

The instability of return distributions evidenced in this study is consistent with Young and Graff (1995), who suggest that real estate return distributions are not stable over time but vary from period to period, and also with Low (1998) who suggests that common stocks return distributions are skewed and the skewness may vary significantly over time. Moreover, the distributional characteristics of Direct Property returns found in this study are not dissimilar to those in Newell (1998).

The different degrees of skewness of return distributions across different assets and the instability of return distributions over time suggest that it would be problematic and misleading to ignore distribution analysis and simply apply standard deviation as the risk measurement in the process of assessing assets performance and constructing optimal portfolio, which constitute the basis of forming investment strategies.

Risk measurement and risk-adjusted performance

Table 3 shows the volatility measured by standard deviation and the downside risk measured by semi-deviation for assets in Portfolio A and Portfolio B.

Table 3: Volatility and downside risk

	Portfolio A (December 1985 - June 2004)					
	LPTs		Direct Properties		Common Stocks	
Standard Deviation	10.17%	(2)	9.36%	(3)	17.23%	(1)
Semi-deviation (TR1)	1.32%	(3)	2.34%	(2)	4.06%	(1)
Semi-deviation (TR2)	4.13%	(3)	5.47%	(2)	7.65%	(1)
	Portfolio B (July 1994 - October 2004)					
	Commercial LPTs		Retail LPTs		Industrial LPTs	
Standard Deviation	6.51%	(3)	11.84%	(1)	8.99%	(2)
Semi-deviation (TR1)	0.56%	(2)	2.75%	(1)	0.55%	(3)
Semi-deviation (TR2)	3.27%	(2)	5.71%	(1)	3.21%	(3)

Notes:
1. Figures in parentheses are riskiness ranking;
2. TR1 represents Target Return of 0% and TR2 represents a Target Return of 8%.

Of relevance and importance is that the ranking of assets in terms of riskiness changes with different approaches of risk measurement. For example, in Portfolio A, if the focus is volatility as measured by standard deviation, the least risky asset is Direct Properties. However, if the focus is downside risk as measured by semi-deviation, either with TR1 (0%) or TR2 (8%) as the target return, the least risky asset will change to LPTs.

Similar results are found for Portfolio B. The least risky asset is Commercial LPTs when the focus is volatility and it will change to Industrial LPTs if the focus is downside risk with either TR1 or TR2 as the target return.

The above results suggest that a portfolio manager will have a very different risk perception towards the assets in the portfolio if the main concerns are 'loss' and downside risk rather than 'uncertainty' and return volatility.

Table 4 presents the results of the performance analysis.

Table 4: Performance analysis

	Portfolio A (December 1985 - June 2004)					
	LPTs		Direct Properties		Common Stocks	
Annualised Return	12.53%	(2)	10.12%	(3)	12.89%	(1)
	Return Risk Ratio					
Standard Deviation	1.2	(1)	1.1	(2)	0.7	(3)
Semi-deviation (TR1)	9.5	(1)	4.3	(2)	3.2	(3)
Semi-deviation (TR2)	3.0	(1)	1.9	(2)	1.7	(3)
	Portfolio B (July 1994 - October 2004)					
	Commercial LPTs		Retail LPTs		Industrial LPTs	
Annualised Return	10.79%	(3)	11.99%	(2)	14.52%	(1)
	Return Risk Ratio					
Standard Deviation	1.7	(1)	1.0	(3)	1.6	(2)
Semi-deviation (TR1)	19.1	(2)	4.4	(3)	26.2	(1)
Semi-deviation (TR2)	3.3	(2)	2.1	(3)	4.5	(1)

Notes:

1. Figures in parentheses are riskiness ranking;
2. TR1 represents Target Return of 0% and TR2 represents a Target Return of 8%.

The annualised returns are time-weighted average returns without being adjusted for the risks undertaken. Risk-adjusted performance is provided by the return-risk ratio, which is the return relative to per unit of risk undertaken.

As shown in Table 4, in Portfolio A, Common Stocks are the best performer and Direct Properties are the worst performer based on unadjusted raw returns. However, LPTs become the best performer and Common Stocks become the worst performer if risk is taken into accounts, with risk being either volatility as measured by standard deviation or downside risk measured by semi-deviation.

For Portfolio B, based on raw returns, Industrial LPTs are the best performer and the Commercial LPTs are the worst. However, Retail LPTs become the worst performer if risk is taken into accounts. Furthermore, which asset has the best risk-adjusted performance depends on how risk is defined. For example, if risk is defined as volatility measured by standard deviation, Commercial LPTs have the best risk-adjusted performance. However, Industrial LPTs become the best performer if risk is defined as adverse outcomes measured by downside semi-deviation, with either TR1 or TR2.

For Portfolio A, although semi-deviation or standard deviation does not make difference in the ranking of assets in terms of risk-adjusted performance, the relative performance of one asset to another does vary significantly depending on whether semi-deviation or standard deviation is considered as the risk. For example, the risk-adjusted performance of LPTs is only marginally higher than that of Direct Properties if risk is measured by standard deviation, but doubles that of Direct Properties if risk is measured by semi-deviation with a target return of 0% (TR1) and is more than one and half times that of Direct Properties if risk is measured by semi-deviation with a target return of 8% (TR2), as shown in Figure 1.

Figure 1: Risk-adjusted performance: Portfolio A (December 1985 - June 2004)

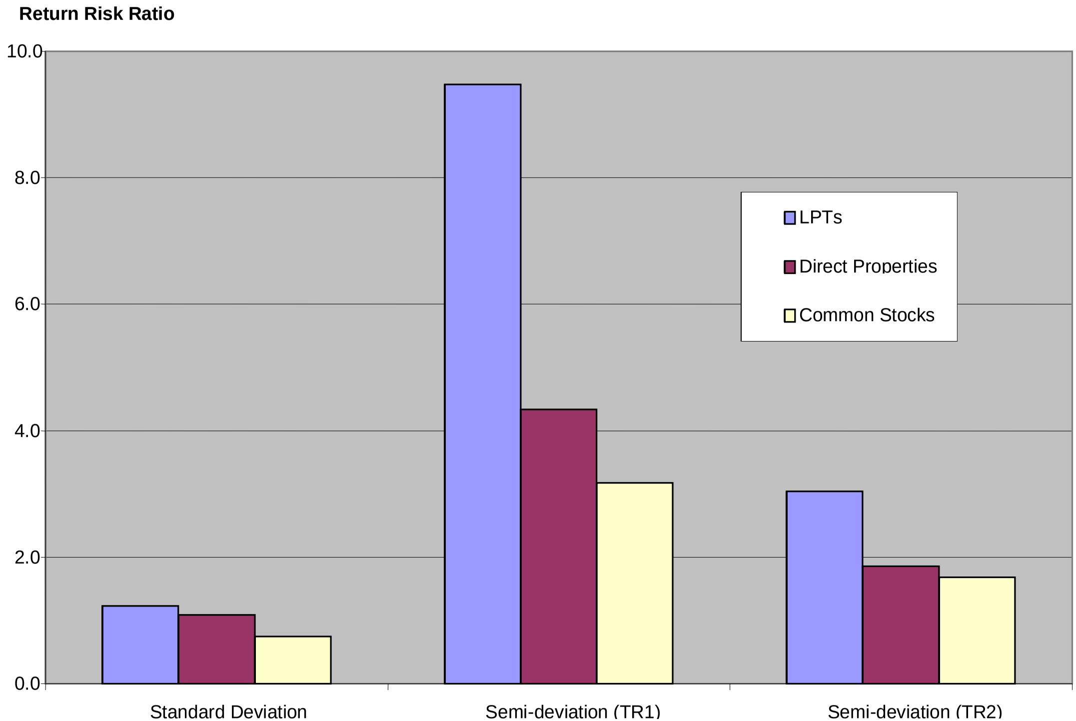


Figure 2: Efficient Frontiers - Portfolio A
(LPTs, Direct Properties and Common Stocks)

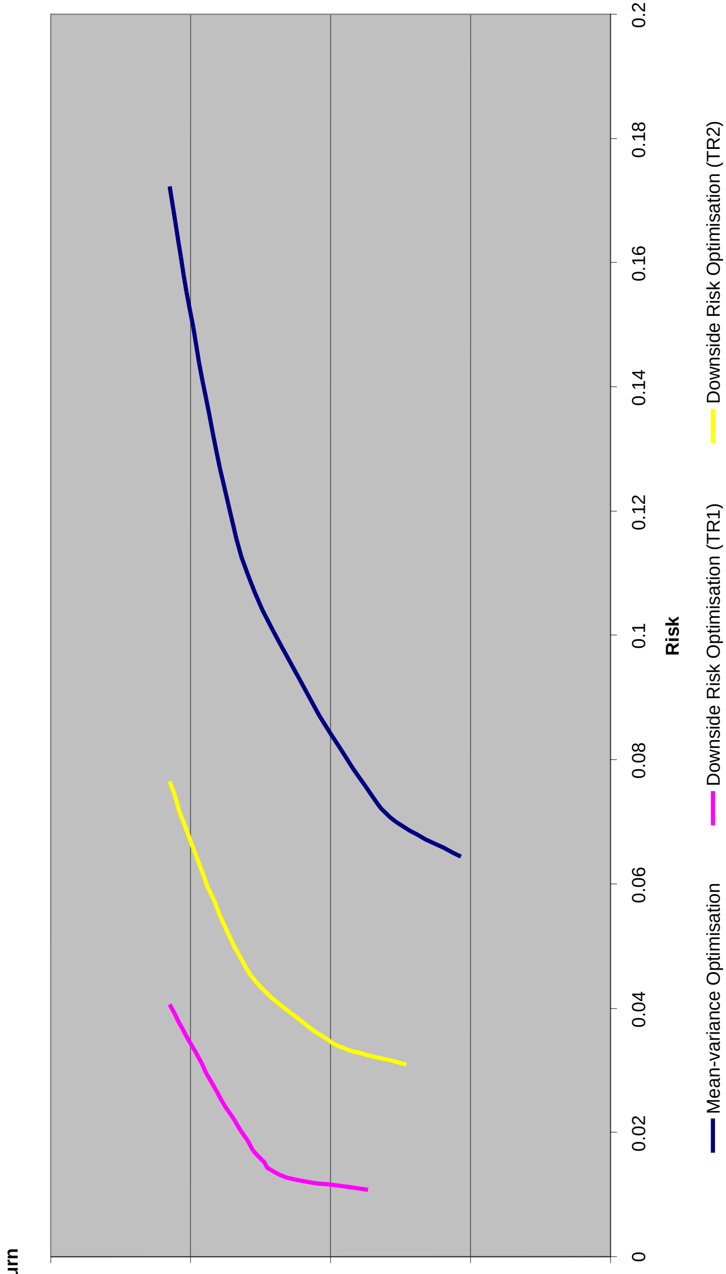
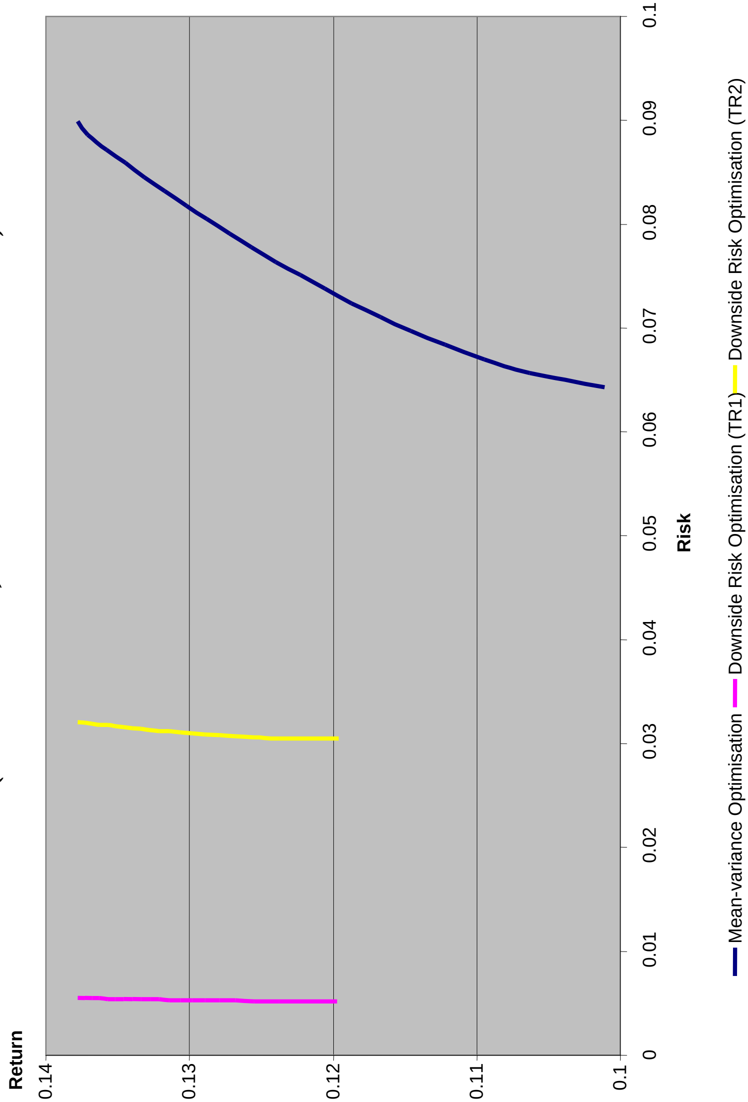


Figure 3: Efficient Frontiers - Portfolio B
(Commercial LPTs, Retail LPTs and Industrial LPTs)



Therefore, to get a clear picture of asset performance, risk not only needs to be taken into account but also needs to be clearly defined. This section clearly demonstrates how standard deviation as the risk measurement may provide false information regarding assets risk/return profiles and result in misleading conclusions to investors whose main concerns are adverse outcomes and downside risk.

Portfolio Construction

The convex efficient frontiers computed based on the classical mean-variance optimisation and the downside risk optimisation algorithms are shown in Figure 2 (Portfolio A) and Figure 3 (Portfolio B).

Two points are apparent from the graphical comparison in the above two figures. Firstly, the convexity of the lower and upper tails of the downside risk curves is stretched vertically along the return axis. That is, for a given range of risk, downside risk curves provide a wider range of returns than mean-variance curves, suggesting that returns are more sensitive to any changes in the level of risk under the framework of downside risk.

Secondly, for downside risk curves, as target return increases, the convexity of the lower and upper tails of the downside risk curves is stretched horizontally along the risk axis. That is, for a given range of risk, the spread of returns becomes narrower as target return increases, and returns become less sensitive to any changes in the level of risk. The second point regarding the convexity of downside risk and mean-variance curves is similar to findings documented in Sing and Ong (2000).

Since downside risk and mean-variance use different risk measures, it is not directly comparable as to which of the two approaches produces less risky portfolios at a given level of expected return. However, a comparison of the different compositions of the optimal downside risk portfolio and the optimal mean-variance portfolio for the same level of expected return would easily demonstrate how the concept of downside risk could make a difference in the construction of optimal portfolios. Table 5 provides such comparisons.

Table 5: Portfolio compositions

	Portfolio A								
Expected Returns	Mean-variance Optimisation			Downside Risk Optimisation (TR1)			Downside Risk Optimisation (TR2)		
	LPTs	Direct Properties	Common Stocks	LPTs	Direct Properties	Common Stocks	LPTs	Direct Properties	Common Stocks
12.50%	*73.82%*	*18.29%*	*7.89%*	*84.15%*	*15.85%*		*82.83%*	*16.16%*	*1.01%*
12.60%	*76.02%*	*14.67%*	*9.31%*	*88.21%*	*11.79%*		*84.78%*	*12.60%*	*2.62%*
12.70%	*78.23%*	*11.04%*	*10.73%*	*92.28%*	*7.72%*		*86.73%*	*9.03%*	*4.24%*
12.80%	*80.43%*	*7.41%*	*12.15%*	*96.34%*	*3.66%*		*88.68%*	*5.47%*	*5.86%*
12.90%	*82.64%*	*3.79%*	*13.57%*	*98.68%*		*1.32%*	*90.63%*	*1.90%*	*7.47%*

	Portfolio B								
Expected Returns	Mean-variance Optimisation			Downside Risk Optimisation (TR1)			Downside Risk Optimisation (TR2)		
	Commercial LPTs	Retail LPTs	Industrial LPTs	Commercial LPTs	Retail LPTs	Industrial LPTs	Commercial LPTs	Retail LPTs	Industrial LPTs
11.90%	*44.70%*	*12.08%*	*43.22%*	*46.09%*		*53.91%*	*46.06%*	*0.68%*	*53.26%*
12.00%	*42.17%*	*12.03%*	*45.80%*	*45.29%*		*54.71%*	*45.14%*	*0.60%*	*54.26%*
12.10%	*39.64%*	*11.98%*	*48.38%*	*42.75%*		*57.25%*	*42.64%*	*0.40%*	*56.96%*
12.20%	*37.10%*	*11.94%*	*50.96%*	*40.20%*		*59.80%*	*40.15%*	*0.20%*	*59.65%*
12.30%	*34.57%*	*11.89%*	*53.53%*	*37.66%*		*63.34%*	*37.66%*		*62.34%*

Notes:
1. TR1 represents Target Return of 0% and TR2 represents a Target Return of 8%.

As shown in Table 5, for Portfolio A, downside risk optimisation, as compared to mean-variance optimisation, suggests a significantly increased weight allocation to LPTs at each level of expected return at the expense of a significantly decreased weight allocation to Common Stocks and a marginally decreased weight allocation to Direct Properties, more so if the target return is lower. For example, at 12.50% expected return and with a target return of 8% (TR2), downside risk optimisation suggests a weight allocation of 82.83% to LPTs compared to 73.82% as suggested by mean-variance optimisation, a weight allocation of 16.16% to Direct Properties compared to 18.29%, and a weight allocation of 1.01% to Common Stocks compared to 7.89%. At the same level of expected return, if the target return is 0% (TR1), the weight allocation to LPTs will further increase to 84.15%, and the weight allocation to Direct Properties will further decrease to 15.85% with non-allocation to Common Stocks, as suggested by downside risk optimisation.

It is worth noting that the above asset classes are selected for illustration purposes and also for data convenience. In reality, asset allocations also take into account the actual weights of different asset classes. Since real estate (both public and private) by itself only accounts for a small portion of the entire investment universe, the total weight allocated to real estate has been constrained in the practice of practically constructing a multi-asset portfolio. This weight has recently been raised from about 8% to around 10% globally due to the appealing risk/return profile of real estate assets, which has partly contributed to the continued yield firming of real estate assets worldwide with weight of money competing for limited real estate assets.

For Portfolio B, downside risk optimisation, as compared to mean-variance optimisation, suggests a significantly increased weight allocation to Industrial LPTs and a marginally increased weight allocation to Commercial LPTs at the expenses of a significantly decreased weight allocation to Retail LPTs, more so if the target return is lower. For example, at 11.90% expected return with a target return of 8% (TR2), downside risk optimisation suggests a weight allocation of 53.26% to Industrial LPTs compared to 43.22% as suggested by mean-variance optimisation, a weight allocation of 46.06% to Commercial LPTs compared to 44.70%, and a weight allocation of 0.68% to Retail LPTs compared to 12.08%. At the same level of expected return, if the target return is 0%, the downside risk optimisation will suggest non-allocation to Retail LPTs but to further increase the weights to 53.91% to Industrial LPTs and 46.09% to Commercial LPTs.

The significant difference in the composition of the optimal downside risk portfolio and the optimal mean-variance portfolio at each given level of expected return clearly demonstrates how the concept of downside risk could prevent portfolio managers, whose target is to minimise downside risk rather than volatility, from drawing flawed conclusions and making wrong decisions.

IMPLICATIONS

The results from this study provide significant implications for LPT investment strategies.

To pick up outperforming assets, portfolio managers need to compare the risk-adjusted performance rather than raw returns of these assets. Since the distribution of asset returns is generally asymmetric and may vary significantly over time, standard deviation has proved to be a poor measurement of risk. Investors whose main concerns are adverse outcomes ought to focus on downside semi-deviation when measuring the level of risk undertaken for their investments. Ignoring analysis of return distributions and simply applying standard deviation as risk measurement could lead to false perception of asset risk/return profiles resulting in poor buy/sell investment strategies. The results from this study suggest the significant outperformance of LPTs compared to Direct Properties and Common Stocks when performance is adjusted to downside risk, providing support to LPT investments.

The concept of downside risk also proves to be a valuable construct to portfolio construction. Investors whose main concerns are adverse outcomes should apply downside risk optimisation algorithm as employed in this study to the construction of optimal portfolios. The mean-variance optimisation algorithm may suggest flawed weight allocation to each of the assets in the portfolio which in turn leads to poor buy/sell decisions and inferior LPT investment strategies. The results from this study suggest a significant increase in the weight allocation to LPTs in an optimal portfolio resulting from downside risk optimisation algorithm, supporting the case of LPT investments in a mixed-asset portfolio.

In fact, Markowitz (1959) recognised the inefficiencies in the traditional mean-variance optimisation algorithm, and suggested a semi-variance measure of risk that focuses only on the outcomes falling below a target rate of return, which is an intuitively more appealing alternative. However, this alternative measure has not gained much attention, due to the implicit assumption of symmetric distribution of asset returns, and also statisticians' greater familiarity with the standard deviation and the added cost of computation time to calculate semi-variances. The results from this study reinforce the importance of downside risk concept in the portfolio analysis involving LPTs.

Emerging markets respond more rapidly to negative news but more sceptical to positive news with less profound response, suggesting a greater tendency towards the risk of downside. Therefore, the above practical implications shall also prove a useful reference to portfolio managers and researchers who are interested in the European and Asian markets where Real Estate Investment Trusts (REITs) are emerging.

CONCLUSIONS AND FURTHER RESEARCH

This study examines Australian LPTs in the context of downside risk and provides significant implications for LPT investment strategies.

It is found that the return distributions of assets under examination are asymmetric and may vary significantly over time, highlighting the importance of the concept of downside risk. This study further demonstrates the significance of differentiating downside risk from uncertainty or volatility as measured by standard deviation in the process of assessing asset performance and constructing optimal portfolios. It illustrates how focusing on the downside risk could prevent LPT investors from making poor investment decisions if they perceive risk as adverse outcomes.

The results of this study suggest that, under the framework of downside risk, LPTs significantly outperform Direct Properties and Common Stocks. Moreover, downside risk optimisation algorithm suggests a significantly increased weight allocation to LPTs in a mixed-asset portfolio at a given level of expected return, compared to mean-variance optimisation algorithm. These results provide support to LPT investments.

Being the first study employing downside risk concept in the context of LPT investment strategies, it complements research literature in the field of LPT studies. The significant practical implications for LPT investment strategies highlighted in this study shall also prove a useful reference to portfolio managers and researchers who are interested in the European and Asian markets where Real Estate Investment Trusts (REITs) are emerging, with assets having a greater tendency towards risk of downside in the emerging markets.

An area of interest for further studies is to apply de-smoothing techniques to the downside risk framework for Direct Properties. Due to illiquidity and lack of transactions, return indices for Direct Properties are generally appraisal based, the appraisal-smoothing and temporal aggregation will result in understated risk estimates for Direct Properties. This issue has been well addressed and relevant techniques have been developed to improve standard deviation based risk estimation, for example, Newell and MacFarlane (1998), Newell and Webb (1996), Newell and MacFarlane (1996), Newell and MacFarlane (1995), Newell and MacFarlane (1994), etc.

It would be interesting to investigate the impact of appraisal smoothing on the semi-deviation based risk estimation and to take into account such impacts in relevant studies. Although beyond the scope of this study which is focusing on demonstrating how valuable the construct of downside risk is to LPT investment strategies, the development of de-smoothing techniques and the application of such techniques to the concept of downside risk shall contribute to the literature of property research.

REFERENCES

Alles, L. and Kling, J. (1994). Regularities in the Variation of Skewness in Asset Returns. *Journal of Financial Research*, 17, 427–438.

Bekaert, G., Erb, C., Harvey, C. and Viskanta, T. (1998). Distributional Characteristics of Emerging Market Returns and Asset Allocation. *Journal of Portfolio Management*, 102-116.

Cheng, P. (2001). Comparing Downside-Risk and mean-Variance Analysis Using Bootstrap Simulation. *Journal of Real Estate Portfolio Management*, 7:3, 225-238.

Cheng, P. and Wolverton, M. (2001). MPT and the Downside Risk Framework: A Comment on Two Recent Studies. *Journal of Real Estate Portfolio Management*, 7:2, 125-131.

Chunhachinda, P., Dandapani, K., Hamid, S. and Prakash, A. (1997). Portfolio Selection and Skewness: Evidence from International Stock Markets. *Journal of Banking & Finance*, 21:2, 143-167.

DeFusco, R, Karels, G. and Muralidhar, K. (1996). Skewness Persistence in US Common Stock Returns: Results from Bootstrapping Tests. *Journal of Business Finance and Accounting*, 23:8, 1183-1195.

Domar, E. and Musgrave, R. (1944). Proportional Income Taxation and Risk-Taking. *Quarterly Journal of Economics*, 58:3, 388-422.

Fishburn, P. (1977). Mean-Risk Analysis with Risk Associated with Below-Target Returns. *The American Economic Review*, 67:2, 116-25.

Giliberto, M. (1990). Equity Real Estate Investment Trusts and Real Estate Returns. *Journal of Real Estate Research*, 5:2, 259-263.

Graff, R. (1998). The Impact of Seasonality on Investment Statistics Derived from Quarterly Returns. *Journal of Real Estate Portfolio Management*, 4:1, 1-16.

Harlow, W. (1991). Asset Allocation in a Downside Risk Framework. *Financial Analysts Journal*, 41, 28-40.

Hogan, W. and Warren, J. (1974). Toward the Development of an Equilibrium Capital Market Model Based Semivariance. *Journal of Financial and Quantitative Analysis*, January, 1-11.

Hoskins, C. (1973). Distinctions between Risk and Uncertainty. *Journal of Business Finance*, 5:1, 10-12.

Kritzman, M. (1994). What Practitioners Need to Know about Time Diversification. *Financial Analysts Journal,* 50:1, 14-18.

Levy, H. and Markowitz, H. (1979). Approximating Expected Utility by a Function of Mean Variance. *The American Economic Review,* 69:3, 308-317.

Low, C. (1998). The Bulls and Bears in the Cross-Section of Stock returns: Exploring an Asymmetric Semivariance Risk Factor. Working Paper, Yale School of Management.

Mao, J. (1970). Models of Capital Budgeting: E-V vs. E-S. *Journal of Finance and Quantitative Analysis,* January, 657-675.

Markowitz, H. (1959). *Portfolio Selection,* John Wiley & Sons: New York, NY.

Myer, F. and Webb, J. (1994). Statistical Properties of Returns: Financial Assets Versus Commercial Real Estate. *Journal of Real Estate Finance and Economics*, 8:3, 267-282.

Nawrocki, D. (1991). Optimal Algorithms and Lower Partial Moments: Ex post Results. *Applied Economics*, 23, 465-470.

Newell, G. (1998). The Distributional Characteristics of Australian Commercial Property Returns. *Australian Land Economics Review*, 4:1, 23.

Newell, G. and MacFarlane, J. (1998). The Effect of Seasonality of Valuations on Property Risk. *Journal of Property Research*, 15:3, 167-182.

Newell, G. and MacFarlane, J. (1996). Risk Estimation and Appraisal-smoothing in UK Property Returns. *Journal of Property Research*, 13, 1-12.

Newell, G. and MacFarlane, J. (1995). Improved Risk Estimation Using Appraisal-smoothed Real Estate Returns. *Journal of Real Estate Portfolio Management*, 1:1, 51-57.

Newell, G. and MacFarlane, J. (1994). Property – More Volatile Than You Thought. *JASSA*, March, 25-27 & 37.

Newell, G. and Webb, J. (1996). Assessing Risk for International Real Estate Investments. *Journal of Real Estate Research*, 11:2, 103-115.

Peng, V. (2004). Selectivity, Timing and the Performance of Listed Property Trusts: Implications for Investment Strategies. *Pacific Rim Property Research Journal*, 10:2, 235-255.

Porter, R. (1974). Semivariance and Stochastic Dominance: A Comparison. *The American Economic Review*, 64:1, 200-204.

Raj, M., Forsyth, M. and Tomini, O. (2003). Fund Performance in a Downside Context. *Journal of Investing*, 12:2, 50-57.

Roy, A. (1952). Safety First and the Holding of Asset. *Econometrica*, 20, 431-439.

Scott, R. and Horvath, P. (1980). On the Direction of Preference for Moments of Higher Order Than the Variance. *Journal of Finance*, 35:4, 915-919.

Sharpe, W. (1998). Morningstar's Risk-adjusted Ratings. *Financial Analysts Journal*, 54:4, 21-33.

Sing, T. and Ling, S. (2003). The Role of Singapore REITs in A Downside Risk Asset Allocation Framework, *Journal of Real Estate Portfolio Management*, 9:3, 219-236.

Sing, T. and Ong, S. (2000). Asset Allocation in A Downside Risk Framework. *Journal of Real Estate Portfolio Management*, 6:3, 213-224.

Sivitanides, P. (1998). A Downside-Risk Approach to Real Estate Portfolio Structuring. *Journal of Real Estate Portfolio Management*, 4:2, 159-168.

Wheaton, W. and Torto, R. (1989). Income and Appraised Values: A Re-Examination of FRC Returns Data. *AREUEA Journal*, 17:4, 439-449.

Young, M. and Graff, R. (1995). Real Estate is Not Normal: A Fresh Look at Real Estate Return Distributions. *Journal of Real Estate Finance and Economics*, 10, 225-259.