

# **An Exploration of the Relationship between Size and Risk in a Downside Risk Framework Applied to Malaysian Property Shares**

**PACIFIC RIM REAL ESTATE SOCIETY (PRRES) CONFERENCE**

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## **Abstract**

The relationship between size and risk (systematic and unsystematic risk) has received considerable attention in recent literature. However, these studies employ variance as the risk measure, which the appropriateness for using this risk measure is always questioned by researchers and practitioners due to its underlying strict assumptions. Therefore, there is crucial to adopt an alternative risk measure for ascertaining the relationships. The aim of the study is to examine the relationships between size and systematic downside risk and unsystematic downside risk in line with the theoretical sound of this risk measure. The empirical evidences reveal that the size is strongly correlated with unsystematic downside risk. While, there is a weak inverse relationship between size and systematic downside risk.

*Keywords: systematic downside risk, unsystematic downside risk, size, property shares*

## **1. Introduction**

Since the introduction of Modern Portfolio Theory by Markowitz (1952), diversification has become the main issue for investors, particularly institutional investors, in making investment decisions. Consequently, Sharpe (1963) proposed a linear model that provides a better understanding for investors on risk and diversification in which the total risk of asset  $i$  is decomposed into systematic risk and unsystematic risk. Systematic risk is an undiversifiable risk, which is attributed with a common factor. On the other hand, unsystematic risk is a diversifiable risk, which is also known as specific risk and it can be totally eliminated via a well diversified portfolio (Brown & Matysiak, 2000, Hargitay & Yu, 1993).

Recently, there have been many attempts to demonstrate the relationship between size and risk. For instance, Conover et al. (1998) found that differences between large firms and small firms in terms of return and risk are statistically significant. Litt et al. (1999)

provided a plausible explanation for this scenario, which revealed that size has a moderate negative correlation with unsystematic risk. This is consistent with findings by Byrne & Lee (2003), Chaudhry et al. (2004) and Malkiel & Xu (1997), who they found a negative relationship between size and specific risk.

Conversely, Gyuorko & Nelling (1996) found a positive and statistically significant relationship between size and systematic risk. Byrne & Lee (2003) also found a positive and statistically significant relationship between size and systematic risk. Interestingly, this relationship became weak and negative when investment characteristics were controlled. Similarly, Litt et al. (1999) also found a weak negative correlation between beta and size.

Therefore, there is no consensus for a relationship between size and systematic risk. One of the possible explanations is that these studies employ variance as the risk measure. Variance is currently the most widely used measure of portfolio risk and it has received the considerable attention from researchers and practitioners (Evans, 2004). But the use of variance as a risk measure is constrained by several strict assumptions: investors have a constant quadratic utility function and asset return distributions are normally distributed. Many finance and real estate literature have rejected both assumptions (Lee et al., 2005).

A survey conducted by Mao (1970) reported that investors are more concerned about the probability of return being lower than a target rate of return. In other words, investors dislike downside volatility and the main concern for most investors is downside risk, which is the likelihood of returns falling below a target rate of return (Byrne & Lee, 2004). Markowitz (1959) also recognised the importance of this argument and suggested the use of semi-variance, or lower partial moment, which is more appealing than variance. As a result, downside risk appears to be a more robust and sensible risk measure than variance; it is suggested that it used in portfolio analysis (Lee et al., 2005).

The appropriateness of using downside risk was also demonstrated by Hogan & Warren (1974) and Bawa & Linderberg (1977). They generalised the downside risk (lower partial moment) into the Capital Asset Pricing Model (CAPM) and developed a mean-lower partial moment capital asset pricing model (D-CAPM). Nantell & Price (1979) and Price et al., (1982) examined the difference between the systematic risks that are derived in a downside risk framework and a mean variance framework. Their findings depicted that systematic risk in a downside risk framework differs from systematic risk in a mean variance framework if the return distributions are in lognormal form.

A growing body of research has also demonstrated the superiority of systematic downside risk than traditional systematic risk. These studies also suggested the use of downside beta (systematic downside risk) as an alternative for traditional beta in portfolio management (Bhardwaj & Brooks, 1993, Cheng, 2005, Chiang et al., 2004, Conover et al., 2000, Estrada, 2000, 2002, Harlow & Rao, 1989).

However, there is limited literature about the relationship between size and downside risk. Devaney & Lee (2005) probably conducted the first study that examined the relationship

between real estate portfolio size and downside risk. Their study replaced variance by downside risk due to the hypothesis that the risk for a fund manager is the risk of underperformance of the benchmark rather than the volatility of returns of the portfolio. They used Monte Carlo simulation and the returns from 1728 properties over the period 1995-2004 in the Investment Property Databank (IPD) database. The results indicated that the increase in portfolio size reduced the portfolio's downside risk (total risk). Importantly, to date, there is no study of the implications of size in reducing systematic risk and unsystematic risk in a downside risk framework.

The aim of this study is to examine the relationship between size and risk (systematic and unsystematic risks) in a downside risk framework. In Sections 2 and 3, the concept of systematic downside risk and unsystematic downside risk are provided. Section 4 discusses the data and then introduces the methodology used in this study. The next section empirically tests the relationship between size and systematic risk and unsystematic risk in a downside risk framework. Section 6 summarises the findings and provides a conclusion.

## 2. The Concept of Systematic Downside Risk

In the Mean Variance Analysis framework, Sharpe (1964) proposed that the expected return of asset  $i$  in CAPM is estimated as:

$$E(R_i) = R_f + \frac{COV(R_i, R_m)}{Var(R_m)} (E(R_m) - R_f) \quad (1)$$

where  $COV(R_i, R_m)$  = Covariance of returns on the market portfolio with returns on security  $i$

$E(R_i)$  = Expected return on asset  $i$

$E(R_m)$  = Expected return on the market portfolio

$Var(R_m)$  = Variance of returns on the market portfolio

$R_f$  = Risk free rate of return

usually simplified and presented as follow:

$$E(R_i) = R_f + \beta_i (E(R_m) - R_f) \quad (2)$$

where  $\beta_i$  is the beta, which is computed by using  $COV(R_i, R_m)/Var(R_m)$ .<sup>1</sup>

In the downside risk framework, semivariance is used as the risk measure. Bawa & Linderberg (1977), Harlow & Rao (1989) and Hogan & Warren (1974) generalised

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<sup>1</sup> See Elton & Gruber (1995) and Estrada (2002) for the details of beta computation.

downside risk into CAPM and proposed that the expected return of the asset  $i$  in Mean Lower Partial CAPM (or D-CAPM) is estimated from the following:

$$E(R_i) = R_f + \frac{CVS_{R_f}(R_i, R_m)}{SV_{R_f}(R_m)} (E(R_m - R_f)) \quad (3)$$

where  $CVS_{R_f}(R_i, R_m)$  = Cosemivariance of returns on the market portfolio with returns on security  $i$   
 $SV_{R_f}(R_m)$  = Semivariance of returns below  $R_f$  on the market portfolio  
 $\frac{CVS_{R_f}(R_i, R_m)}{SV_{R_f}(R_m)}$  = Downside Beta ( $\beta_i^D$ )

The expected return of the asset  $i$  in Equations (1) and (3) is computed in exactly in the same way in both frameworks except for the estimation of beta. As such, beta in the downside risk framework is defined as  $CVS_{R_f}(R_i, R_m) / SV_{R_f}(R_m)$  and Equation (3) can be simplified as follows:

$$E(R_i) = R_f + \beta_i^D (E(R_m - R_f)) \quad (4)$$

where  $\beta_i^D$  is the downside beta.

However, Estrada (2002) highlighted the limitations of the existing estimation of downside beta, which Bawa & Linderberg (1977), Harlow & Rao (1989) and Hogan & Warren (1974) defined as co-semivariance as follows:

$$CVS_{R_f}(R_i, R_m) = E\{(R_i - R_f) \cdot \text{Min}[(R_M - R_f), 0]\} \quad (5)$$

Clearly, Equation (5) is in asymmetry form. Thus, the cosemivariance between two assets  $i$  and  $M$  is different from the cosemivariance between asset  $M$  and  $i$  (Estrada, 2000, 2002, Lee et al., 2005, Nawrocki, 1992). As a result, Estrada (2002) proposed a replacement of the CAPM beta by the ratio below (in symmetric form) in order to obviate the limitations of the Equation (5):

$$\beta_i^D = \frac{E\{\text{Min}[(R_i - \mu_i)] \text{Min}[(R_M - \mu_M), 0]\}}{E\{\text{Min}[(R_M - \mu_M), 0]^2\}} \quad (6)$$

where  $R_i$  is return of asset  $i$  at the time  $t$ ,  $\mu_i$  denotes the risk free rate or the rate of return of benchmark.

### 3. The Concept of Unsystematic Downside Risk

One of the essential properties of CAPM is to facilitate risk decomposition and quantification in which total risk can be decomposed into two orthogonal components: a market risk and firm-specific residual. A time-series regression for CAPM is as follows:

$$R_i - R_f = \alpha_i + \beta_i(R_M - R_f) + \varepsilon_i \quad (7)$$

where  $R_i$  = return of asset  $i$  at the time  $t$ ,  $R_f$  = risk-free rate,  $\alpha_i$  = non-index related return to asset  $i$ ,  $\beta_i$  = beta of asset  $i$ ,  $R_M$  = return to market index at the time  $t$ ,  $\varepsilon_i$  = residual return of asset  $i$  at the time  $t$ .

Taking the variance of both sides; the variance of returns on asset  $i$  is shown as:

$$Var(R_i) = \beta_i^2 Var(R_M) + Var(\varepsilon_i) \quad (8)$$

where  $Var(R_i)$  is the variance of the asset  $i$ ,  $Var(\varepsilon_i)$  is volatility measure for unsystematic risk.<sup>2</sup>

As discussed above, the computation of CAPM and D-CAPM are the exactly same except for beta. Therefore, the unsystematic downside risk can also be estimated by amending Equation (8) in which total risk is substituted by total downside risk; beta is changed to downside beta; variance of the market portfolio is replaced by semivariance of the market portfolio and unsystematic risk is substituted by unsystematic downside risk. The relationships between total downside risk, systematic downside risk and unsystematic downside risk are written as follow:

$$SV_{R_f}(R_i) = \beta_i^{D^2} SV_{R_f}(R_m) + SV_{R_f}(\varepsilon_i) \quad (9)$$

Where  $SV_{R_f}(R_i)$  = Total Downside Risk (Semivariance)

$SV_{R_f}(R_m)$  = Semivariance of market portfolio

$SV_{R_f}(\varepsilon_i)$  = Unsystematic downside risk

## 4. Data and Methodology

### 4.1 Data

In this study, annual returns from Malaysian Property Shares (PSs) were utilised. As at 31<sup>st</sup> December 2003, there were 90 property companies listed on Bursa Malaysia (formerly known as Kuala Lumpur Stock Exchange). From which 30 listed property

<sup>2</sup> See Beckers (1996), Chaudhry et al. (2004) and Sanders et al. (2001) for the details.

shares have been selected in this study. The analysis spans the 1992-2003 time period in which covers the boom (1993) and recession (1997) phases of the most recent property shares cycle in Malaysia.

It must be noted that Bursa Malaysia experienced highly speculative activity in 1993; the daily turnover surged to RM4.8 billion on 22 December 1993 (Central Bank of Malaysia, 1994b). There was a steep rise in share prices due to the speculative activities (Central Bank of Malaysia, 1994a). In addition, the monthly returns for most PSs in 1993 were exceptionally high, for example, the monthly return of AHPLANT in October 1993 at 117.54%. This affected the stabilisation of the money market and the exchange rate (Department of Valuation and Property Services Malaysia, 1994). Hence, annual data is utilised in this study in order to avoid the biasing effect of the speculation period for the stock market in 1993 and better reflect the true potential performance of PSs.

Additionally, market capitalisations of individual PSs were employed as indicators of size and Property Stock Index was used as the market benchmark. All of these data were obtained from Bursa Malaysia. 3-month Treasury Bill (TB) was used as the risk-free rate, which was obtained from Central Bank of Malaysia.

## 4.2 Methodology

As discussed above, the rationale of using variance is doubtful if the asset return distributions are not symmetrically or normally distributed. As such, it is crucial to examine the asset return distribution to establish whether return is normally or asymmetrically distributed.

Several tests can be used in order to examine the normality of asset return distributions. In this study, skewness, kurtosis and Jera-Bera Test were used for examining the PSs return distributions. This is consistent with the methodology of Brown & Matysiak (2000) and Kishore (2004).

### Skewness

Skewness characterises the degree of asymmetry of a distribution around its mean. Zero skewness indicates the distribution is symmetry. Whereas, positive skewness indicates a distribution with an asymmetric tail extending toward right. Conversely, negative skewness indicates a distribution with an asymmetric tail extending toward left. Skewness is computed as follow:

$$S = \frac{1}{T-1} \sum_{i=1}^T \frac{(R_i - \bar{R})^3}{\sigma^3} \quad (10)$$

where  $R_i$  is the return for asset  $i$ ,  $\bar{R}$  is the mean return of asset  $i$ ,  $\sigma$  is the standard deviation of asset  $i$  and  $T$  is total number of returns.

## Kurtosis

Kurtosis describes the degree of flatness or peakedness of an asset return distribution. Kurtosis is estimated from the following:

$$K = \frac{1}{T-1} \sum_{i=1}^T \frac{(R_i - \bar{R})^4}{\sigma^4} \quad (11)$$

where  $R_i$  is the return for asset  $i$ ,  $\bar{R}$  is the mean return of asset  $i$ ,  $\sigma$  is the standard deviation of asset  $i$  and  $T$  is total number of returns.

## Jarque-Bera Test

Jarque & Bera (1980, 1987) proposed a combination of skewness and kurtosis (is also known as the Jarque-Bera Test) in order to examine the normality of a distribution. The Jarque-Bera statistic is computed as follow:

$$JB = \frac{n}{6} \left[ S^2 + \frac{(K-3)^2}{4} \right] \quad (12)$$

where  $S$  is a measure of skewness,  $K$  is a measure of kurtosis and  $n$  is the sample size. The Jarque-Bera statistic has a chi-squared distribution with two degrees of freedom (one for skewness, one for kurtosis).

## 4.3 Downside Risk

The downside risk (total risk) can be estimated by Lower Partial Moment, which is defined by Bawa (1975) and Fishburn (1977):

$$\begin{aligned} LPM_{\alpha}(\tau, R_i) &= \int_{-\infty}^{\tau} (\tau - R)^{\alpha} dF(R) \\ &= \frac{1}{T-1} \sum_{i=1}^T [Max(0, (\tau - R_i))]^{\alpha} \end{aligned} \quad (13)$$

where  $dF(R)$  is the cumulative distribution function of the investment return  $R$ ,  $\tau$  is the target return,  $\alpha$  is the degree of the LPM,  $R_i$  is the return of asset  $i$  and  $T$  is total number of returns.

Notably, semi-variance is a special case of the more general LPM in which the  $\alpha$  value is equal to 2. Thus, it can also be referred to as a target semi-variance (Harlow, 1991). In this study, the degree of the LPM is equal to 2 in order to estimate the semivariance. Furthermore, the  $\tau$ , target rate is set as the risk-free rate.

#### 4.4 Regression Model

In this study, two regression models were employed in order to ascertain the relationship between size and systematic downside risk and unsystematic downside risk. Both systematic downside risk and unsystematic downside risk are regressed against size. The regression models are estimated as follows:

$$\text{Log}(\text{SystematicDownsideRisk}) = \alpha + \beta_i \text{Log}(\text{Size}) + e_i \quad (14)$$

$$\text{Log}(\text{UnsystematicDownsideRisk}) = \alpha + \beta_i \text{Log}(\text{Size}) + e_i \quad (15)$$

where systematic downside risk ( $\beta_{Di}$ ) and unsystematic downside risk are derived from Equation (6) and Equation (9) respectively, size is the actual size of the PSs;  $\alpha$ ,  $\beta_i$  and  $e_i$  are estimated from the models.

### 5. Results and Analysis

#### 5.1 The Distribution of the Asset

Table 1 reveals the distribution of different size groups (Small, Medium and Large) from 1992 to 2003. In general, all different PSs size groups exhibited positive skewness. Interestingly, all individual PSs also displayed a positive skewness except SIMEPTY (-0.04) and FIMACORP (0).<sup>3</sup>

It is not surprising that no size group revealed a kurtosis with 3; while all size groups displayed a kurtosis of more than 3 (leptokurtosis). The heterogeneity in kurtosis was also apparent; the Medium group showed 6.94 kurtosis; while the Large group exhibited 4.70 kurtosis. It is more noticeable for individual PSs, for example, PTGTIN had 9.37 kurtosis whereas SIMIPTY revealed -0.71 kurtosis.

Consistently, all size groups were statistically significant in the Jarque-Bera Test. As a result, the assumption that these size groups are normally distributed should be rejected by the Jarque-Bera test. Surprisingly, all individual PSs were asymmetrically distributed except FBO (1.54), SPB (2.07), BRAYA (2.74), PARAMOUNT (3.80), CRIMSON (3.91), IGB (4.02), FIMACORP (4.60), BOLTON (4.66) and IOI (5.86).

These results are consistent with the results for developed real estate markets such as United States (U.S.), United Kingdom (U.K.) and Australia where return distributions of real estate (including securitised and unsecuritised real estate) are not necessarily

<sup>3</sup> See Appendix 1 for the details of individual PSs.



normally distributed (Graff et al., 1997, Kishore, 2004, Maitland-Smith & Brooks, 1999, Myer & Webb, 1993, 1994, Peng, 2005, Young & Graff, 1995). In line with this, the assumption of Mean Variance Analysis and the rationale of using variance as risk measure are questionable.

**Table 1: The Distribution of Assets (1992-2003)**

Group(s)/Asset(s)	Skewness	Kurtosis	Jarque-Bera Test
Small	1.94	5.49	17.12*
Medium	2.45	6.94	24.07*
Large	1.66	4.70	17.14*

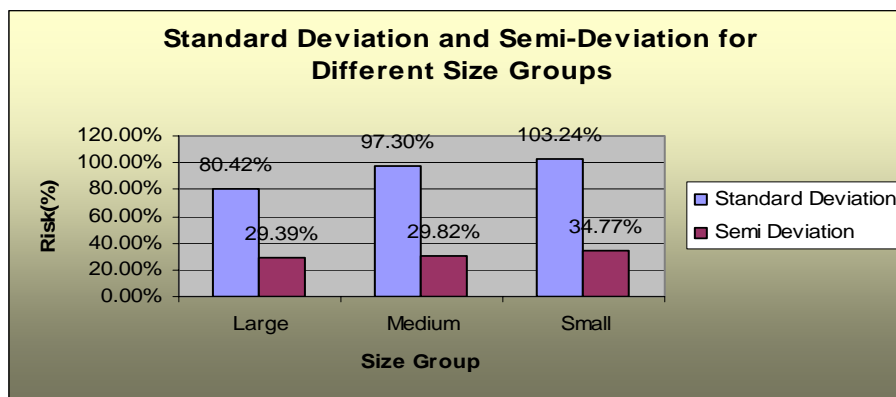
Note: (\*) significant at 5% level

## 5.2 Risk Analysis

According to the Figure 1, the volatilities of assets were substantially lower when downside risk was employed. The semi deviations of all size groups were only 1/3 of the standard deviations for corresponding size groups. These results are consistent with the results of Peng (2005), Sing & Ong (2000) and Sivitanides (1998) in which the variance (standard deviation) is higher significantly than the downside risk for Australian Listed Property Trusts, Singapore real estate and U.S. REITs respectively.

Another point must be noticed is the Large group (80.42%) has a smaller volatility compared to Medium (97.30%) and Small (103.84%). Similarly in the downside risk framework, the semi deviation of the Large group was 29.39%, which was lower than Medium (29.82%) and Small (34.77%). In other words, the Large PSs have lower risk compared to smaller PSs. These results are consistent with the results from Gyourko & Nelling (2003) for standard deviation and Devaney & Lee (2005) for semi-deviation (total downside risk).

**Figure 1: Standard Deviation and Semi-Deviation for Different Size Groups**



### 5.3 Performance Analysis

Table 2 presents the performance analysis of PSs in different size groups from 1992 to 2003. Over this 12-year period, the average return of Large group (24.23%) was slightly higher than Medium (22.61%) and Small (20.96%).

However, average return cannot simply be used for ranking purposes without pondering risk. As a result, in this study, risk-adjusted return was used for this purpose and the risk-adjusted returns were calculated using the Sharpe Ratio and the Sortino Ratio.<sup>4</sup> Using the Sharpe Ratio, it was shown that the Large group was the best performer group compared to the Small and Medium groups on a risk-adjusted basis. Conversely, the Sortino Ratio provided contradictory results, which the Medium group achieved the highest risk-adjusted performance while the Small group was the worst performer.

Thus, the results from Sharpe Ratio and Sortino Ratio are always contradictory. This can be attributed to different risk measures are employed by both ratios. Additionally, this is consistent with the results from Ellis & Wilson (2005) and Stevenson (2001), which Sharpe Ratio and Sortino Ratio exhibit diverge results.

**Table 2: Performance Analysis (1992-2003)**

Asset	Average Return (%)	Sharpe Ratio	Sortino Ratio
Small	20.96	0.2347 (2)	0.6970 (3)
Medium	22.61	0.2324 (3)	0.7582 (1)
Large	24.23	0.2606 (1)	0.7130 (2)

Note: Figures in parenthesis are risk-adjusted ranking.

### 5.4 The Downside Beta and Unsystematic Downside Risk

Table 3 presents the downside beta (systematic downside risk) and unsystematic downside risk of PSs. The downside beta for the small size group was 1.13. This indicates that when market return falls by 1%, this group will fall by 1.13%. Thus, magnifying by 13% the downside swings in the market with respect to the risk free rate. Conversely, the downside betas for Medium and Large size groups were 0.93 and 0.96 respectively. In other words, on average, both groups will fall only 0.95% with a 1% fall in the market. Another important observation is that there is no obvious relationship between downside beta and size. Moreover, the downside beta for various size groups did not vary noticeably.

However, the impact of size was found affect unsystematic downside risk. The Large size group has the lowest unsystematic downside risk (1.38%), which was around half of the

<sup>4</sup> Sharpe Ratio employs standard deviation as the risk measure and can be estimated as: Sharpe Ratio = (return of asset i at the time t – the risk-free rate)/standard deviation of asset i at the time t. Whereas Sortino Ratio utilises semi deviation as the risk measure and is computed as: Sortino Ratio = (return of asset i at the time t – the risk-free rate)/semi deviation of asset i at the time t.

Small group (2.18%). While, the systematic downside risk for Medium group was 1.79%. The overall picture that emerges from Table 3 is that Large PSs have a lower unsystematic risk, but there is no similar noticeable evidence for the downside beta. The importance of size to downside beta and unsystematic downside risk reduction are still vague. Hence, it is essential to investigate this issue in more depth.

**Table 3: Downside Beta and Unsystematic Downside Risk**

Asset	Downside Beta	Unsystematic Downside Risk (%)
Small	1.13	2.18
Medium	0.93	1.79
Large	0.96	1.38

### 5.5 The Relationship between Size and Risk (Downside Beta and Unsystematic Downside Risk)

Table 4 illustrates the empirical relationship between size and risk. Consistent with the results from the previous section, the regression model depicted that downside beta has an insignificant negative relationship with size. In other words, the Large PSs have only a slightly lower systematic downside beta. There is no considerable reduction in systematic downside risk for investors by investing in Large PSs. This confirms the assertions of CAPM in which only unsystematic risk can be eliminated and affected by size. Moreover, this is also consistent with results from Litt et al. (1999) for U.S. REITs and Byrne & Lee (2003) for U.K. property funds by controlling the investment characteristics. But, it counters the findings from Gyuorko & Nelling (1996), which is analysed with Mean Variance Analysis framework.

On the other hand, size has a significant negative correlation with the unsystematic downside risk (-0.3219). This indicates that doubling the size of the PSs will lead to a significant reduction in unsystematic downside risk of just over 32%. In other words, the smaller PSs have larger unsystematic downside risk. This is consistent with the contentions of CAPM and findings from Byrne & Lee (2003), Chaudhry et al. (2004), Litt et al. (1999) and Malkiel & Xu (1997), which are analysed under the Mean Variance Analysis framework.

Interestingly, the size coefficients for downside beta and unsystematic downside risk are quite close with the size coefficients for beta and unsystematic risk that were found by Litt et al. (1999) for U.S. REITs. One of the possible explanations is they employed the Risk-Adjusted Model for their estimation.<sup>5</sup>

<sup>5</sup> Litt et al. (1999) reported that the size coefficients with NAREIT Beta and firm-specific risk were -0.41 and -0.16 respectively.

**Table 4: The Empirical Relationship between Size and Risk**

Variable	Log(Downside Beta)	Log(Unsystematic Downside Risk)
Constant	1.002 (0.9597)	0.8524 (2.2647)
Log(Size)	-0.1191 (0.1113)	<b>-0.3219</b> (0.2627)
R-square	3.93%	5.09%

Note: Figures in parenthesis are Standard Errors.

## 6. Conclusions and Implications

This paper investigates the relationship between size and risk (systematic risk and unsystematic risk) in a downside risk framework. Several important findings can be drawn from the analyses. First, the Malaysian PSs return distributions are like other real estate (securitised and unsecuritised real estate) in developed markets; they are not necessarily normally distributed. As such, the rationale of using variance as the risk measure is precluded if the return distributions are in asymmetric form and it strengthens the motivation to use downside risk, particularly for emerging markets.

Second, the variance (standard deviation) exhibits higher risk for investors. This can be attributed to the inclusion of upside potential in risk estimation under the Mean Variance Analysis framework, which is not logical. It is not surprising that the risk of Malaysian PSs, as an emerging market, is over-estimated considerably by using variance. In line with this, downside risk is suggested to be used as a risk measure particularly for emerging markets.

Third, size is negatively correlated to the unsystematic risk, while there is no similar evidence for systematic risk in a downside risk framework. This supports the assertions of CAPM in which investors only can diversify their unsystematic risk through size investment strategy but would not gain any systematic downside risk reduction via this strategy. In other words, portfolio fund managers and investors can only gain the full unsystematic downside risk diversification benefit by investing in Large Market Capitalisation PSs.

This probably is the first study to explore the relationship between size and risk (systematic risk and unsystematic risk) in a downside risk framework in a real estate context and future work is needed to confirm the relationship. Future research should be directed to improving the model by employing more factors. Larger samples should be employed to help researchers to more accurately assess the relationship between size and systematic risk and unsystematic risk in a downside risk framework.

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## Appendix 1

Table 6: Summary Statistics

PSs	Return	Standard Deviation	Skewness	Kurtosis	JB
<b>Large</b>					
SIMEPTY	11.76%	42.14%	-0.04	-0.71	6.88*
HLPROP	28.62%	127.10%	2.95	9.48	38.38*
L&G	25.60%	108.08%	2.24	6.18	15.09*
IOI	56.61%	122.15%	1.66	2.17	5.86
IGB	10.89%	40.86%	0.05	0.17	4.02
BRAYA	27.36%	72.45%	1.15	2.52	2.74
SPB	9.62%	34.17%	0.25	1.03	2.07
PELANGI	6.29%	54.42%	2.77	8.59	30.96*
FACBRES	21.89%	117.07%	2.97	9.57	39.23*
AMDB	10.95%	85.78%	2.61	8.00	26.15*
<b>Medium</b>					
PGARDEN	3.46%	32.87%	2.84	8.92	33.68*
UMLAND	31.13%	118.43%	2.74	8.03	27.70*
DBHD	15.19%	116.81%	2.75	8.36	29.51*
MUIPROP	12.06%	68.98%	2.29	6.66	17.13*
BOLTON	18.72%	73.87%	1.13	0.94	4.66
NEGARA	12.89%	60.02%	2.36	6.84	18.47*
AHPLANT	68.53%	186.64%	2.05	3.59	8.58*
TALAM	30.73%	133.04%	3.18	10.64	49.34*
PJDEV	18.01%	89.59%	2.29	6.26	15.80*
SDRED	15.38%	92.79%	2.87	9.20	35.77*
<b>Small</b>					
ASIAPAC	15.95%	102.50%	2.69	8.33	28.70*
YTL	51.92%	163.92%	2.80	8.48	30.74*
MENANG	25.50%	115.95%	2.13	4.03	9.60*
FBO	2.66%	46.76%	0.83	3.57	1.54
E&O	33.20%	126.69%	2.61	7.81	25.21*
PTGTIN	45.66%	170.56%	2.94	9.37	37.62*
CRIMSON	4.22%	63.35%	1.38	2.52	3.91
PARAMOUNT	19.25%	69.81%	1.38	2.90	3.80
AHTIN	27.44%	120.05%	2.60	7.89	25.48*
FIMACORP	16.54%	52.77%	0.00	-0.03	4.60

Note: \* significant at 5% level