VOLATILITY SPILLOVER IN AUSTRALIAN COMMERCIAL PROPERTY

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ABSTRACT

Extensive real estate studies have demonstrated the linkages between direct property and capital assets, particularly REITs by emphasising on the common movements in prices. However, the study of volatility spillover between these assets is relatively limited. This study aims to investigate the volatility linkages between Australian commercial property and capital assets by utilising generalised autoregressive conditional heteroskedasticity (GARCH) and Exponential GARCH (EGARCH) over the study period 1985-2006. The results reveal that direct commercial property is strongly influenced by LPTs and bonds. It is also shown that direct property is asymmetric to negative and positive news. These findings have provided additional insights into the knowledge base of real estate risk and portfolio management.

Keywords: Volatility spillover, GARCH, EGARCH, commercial property, Australia

INTRODUCTION

Commercial property is an important asset for investors, particularly institutional investors. In December 2006, almost AUD$167 billion of commercial property in Australia are owned by institutional investors, representing 72% of the total size of core commercial property in Australia (Higgins, 2007). More specifically, the Australian LPT market is the largest player in this industry. In 2006, Australian LPTs managed almost AUD$143 billion commercial property in Australia and overseas (PIR, 2006).

Given the importance of LPTs in the Australian commercial property market, it is reasonable to expect that the performance of commercial property is influenced by the performance of capital assets such as LPTs. A stream of real estate literature has also endeavoured to understand the link between direct property and indirect property. One of the areas that have attracted considerable research interest is price discovery between these assets. A substantial price discovery literature shows that indirect property Granger-caused the returns of direct property (Geltner et al., 2003).

Gyourko and Keim (1992) also found that indirect property has strong explanatory power to the returns of direct property in the U.S. Similar findings are also demonstrated by Barkham and Geltner (1995). Eichholtz and Hartzell (1996) also examined the predictive capacity of real estate shares to appraised-based real estate returns and concluded that the securitised real estate market can predict unsecuritised real estate. This suggests that information is incorporated quicker in indirect property than direct property. A more recent study, however, exhibited divergent results in which securitised real estate has little predictive power for unsecuritised real estate (Tuluca et al., 2000). In Hong Kong, Chau et al. (2001) modelled the price discovery of Hong Kong direct property and failed to find strong evidence of predictive power of securitised real estate to unsecuritised real estate. Most importantly, this study also finds that capital market factors and local economic factors have higher predictive power to direct property returns.

It should be noted that previous studies only emphasise on the first-moment (return), while the second-moment (volatility) could also reflect some new and important information. Importantly, volatility has been viewed as a key variable in many areas of finance (Bollerslev et al., 1992). There is a growing amount of finance literature showing the importance of understanding the attitude of investors towards both expected returns and risk (Asteriou and Hall, 2007). Thus, a large number of studies in the finance literature have been conducted to analyse the pattern of volatility. It also emerges an agreement of volatility clustering in financial time series data in which large changes in returns are followed by other large changes and vice versa in the series. Many studies have also devoted to understand the volatility linkages among financial and macro-economic series. It is also known as volatility spillover. The strong evidence of volatility spillover effects in stock, interest rate and exchange rate returns series has already appeared (Bollerslev et al., 1992, a review).

However, little real estate study has been placed on investigating the volatility linkages between direct property and other capital assets, particularly REITs. The only exception is Bond and Hwang (2003). It reported that there is a similar fundamental volatility process between the securitised and unsecuritised commercial property markets in the U.K.

Therefore, this study aims to examine the volatility spillovers of direct property and capital market assets, especially LPTs. Unlike previous studies in price-discovery, this study is expected to offer further insights into the nature of volatility linkages between these markets. Moreover, an investigation of the volatility spillover effects could provide further evidence to verify whether the derived results from the first-moment (price-discovery) can also be applied to the second-moment.

The remainder of this paper is organised as follows. Section 2 describes the previous literature on volatility spillover in real estate. The data and methodology of this study are discussed in Section 3. Section 4 reports and discusses the results. The final section concludes the paper.

LITERATURE REVIEW

Although volatility spillovers have attracted increasing attention in the recent real estate literature, most studies have focused on volatility spillovers among international real estate markets. Garvey et al. (2001) examined volatility spillover effect among four property stock markets in Asia-Pacific (Australia, Japan, Hong Kong and Singapore) with GARCH models. They found little volatility linkage among these markets and highlighted the diversification opportunities available within these Pacific-Rim markets. Zhu and Liow (2005) also employed GARCH models to investigate the volatility linkage between Hong Kong and Shanghai securitised property markets. They found that the volatility of Hong Kong property shares would spillover to Shanghai property stocks over the study period from 1993 to 2003. However, the sub-period analysis shows that the volatility spillover effect has changed from Shanghai property stocks to Hong Kong property stocks in recent years.

Liow et al. (2005) examined the linkages between Asian and European property stock markets, as well as the degree of short-term interdependence among Asian property and European property stock markets. The study employed a EGARCH (1,1) model and found little cross-volatility spillovers among these markets. Michayluk et al. (2006) utilised an Asymmetric Dynamic Covariance (ADC) model and found a unidirectional volatility spillover from the U.S. securitised real estate market to the U.K. Furthermore, asymmetric in volatility is also demonstrated in which negative and positive shocks (news) influence the markets divergently and the negative news appears to have a stronger effect.

Devaney (2001) found an inverse relationship between changes in interest rate volatility and REIT excess returns with a GARCH-Mean model. Stevenson (2002) provides evidence concerning the volatility linkage 1) between different U.S. REIT sectors and 2) between U.S. REITs and other equity and fixed-income assets. The paper reported that U.S. REITs are strongly linked to small cap and value stocks. However, Cotter and Stevenson (2006) found that the volatility spillover effect is influenced by data frequency. The results also illustrated that the influences of small cap and value stocks are less significant in daily REIT returns. Kallberg et al. (2002) also found a two-way causality in which the results show that the volatility of real estate stocks Granger-cause the volatility of equities and vice verse in several Asian markets. Most importantly, they also found a divergence causality result from return and volatility series, implying missing of a common explanatory factor for both series. In other words, return series and volatility series provide different information.

Additionally, Clayton and Mackinnon (2003) proposed a variance-decomposition procedure to examine the relative importance of property, stocks and bonds to explain the volatility of REITs. The study showed that REITs volatilities are largely affected by stocks, particularly small-cap stocks in recent years. Importantly, property only plays a minor contribution. Similar results are also documented in Australian LPTs by Newell

(2005b). These results are consistent with a recent study in the Hong Kong property share market by Newell et al. (2007).

The volatility spillovers between real estate spot and future markets are also documented by Wong et al. (2007). Similarly to the housing market, Guirguis et al. (2007) also demonstrated volatility spillovers from large city to small city in the Spanish housing market. A recent study has also demonstrated a strong volatility clustering effect in over half of the states in the U.S. (Miles, 2008). The persistence of time-varying volatility is also documented by Dolde and Tirtiroglu (1997), Crawford and Fratantoni (2003) and Wong et al. (2006) for the U.S. and Hong Kong housing markets respectively. Miller and Peng (2006) also found that the estimated volatility series with GARCH models is Granger-caused by home appreciation rate and GDP growth rate based on data for metropolitan statistical area home prices indices exhibiting volatility clustering. The volatility clustering is also evident in the U.K. retail sector (Nigel and Tsolacos, 2005) and U.S. REITs (Najand et al., 2006).

The primary conclusion that can be drawn from the literature review is although numerous studies have enriched our understanding of volatility spillover effect and demonstrated the appropriateness of using GARCH models in the real estate context; no detailed studies have been conducted on the volatility spillover in direct property and capital assets.

DATA AND METHODOLOGY

Consistent with Newell (2005b), the data utilised in this study consists of semi-annual returns of direct property, LPTs, stocks and bonds with regard to no quarterly direct property returns are available prior to Quarter 3 in 1995[1]. The data were obtained for the study period over June 1985-June 2007 from Property Council of Australia as the following:

- Direct commercial property- IPD/PCA Composite Index
- LPTs-ASX/LPT LPT 300
- Stocks-All Ordinaries
- Bonds-All Series, Maturities Bonds

It should be noted that the IPD/PCA Composite Index is an appraisal-based index for direct commercial property in Australia. Similar to the equivalent indices in the U.K. (IPD All Property Index) and U.S. (NCREIF index), there is a downward bias in the volatility of these appraised-based indices. Hence, in this study, the Geltner (1993)'s smoothing

[1] A recent study has demonstrated that GARCH models are sensitive to the data frequency. Hence, employing semi-annual data is one of the limitations of this study that should be borne in mind. However, an investigation of the spillover between LPTs and stocks, as well as bonds is beyond of the scope of this paper, although these assets offer higher frequency of data.

correction method was employed to de-smooth direct property returns. As demonstrated by Geltner (1993):

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

where W is unsmoothing 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 unsmoothing parameter of 0.333 is selected. The unsmoothed returns and appraised-based returns are compared in Figure 1.

Figure 1: Comparison between smoothed and unsmoothed direct commercial returns

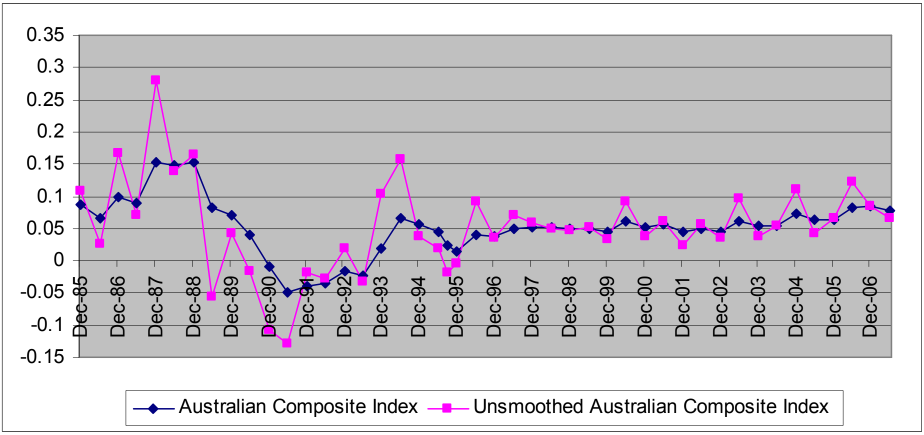

Figure 1 illustrates that unsmoothed returns exhibit higher fluctuation (volatility) in comparison to IPD/PCA composite returns, especially from 1985 to 1994. This indicates that the smoothing issue in the IPA/PCA appraised based return series is severe in which unsmoothed returns display a higher standard derivation than the original IPD/PCA returns. This result is consistent with the findings from a recent study on the PCA Australian commercial property index (Newell, 2005a). Importantly, in terms of the graph, it is clear that there is some preliminary support of volatility clustering in the series in which there are some certain periods that have higher volatility than others.

Nevertheless, unlike to Chau et al. (2001), no de-gearing attempt has been undertaken to de-gear the LPT series with regard to the gearing levels of LPTs are much lower than property stocks and/or real estate operation companies. In December 2006, the average level of gearing in LPTs was at a relatively low level with approximately 36% (PIR, 2007)[2].

METHODOLOGY

It is important to note that it is essential to estimate whether time-varying volatility is present; GARCH modelling is only required instead of ordinary-least squares (OLS) if there is a presence of ARCH/GARCH effect (volatility clustering). As a result, it is important to determine whether direct property return is time-varying with volatility clustering before a GARCH model is employed (Asteriou and Hall, 2007). The volatility clustering or ARCH effect is examined by 1) Ljung-Box test and 2) (Engle, 1982) LM test for ARCH of order of p tests. The Engle (1982) LM test for ARCH is given as follows:

$$\varepsilon_t^2 = \phi_0 + \phi_1 \varepsilon_{t-1}^2 + \phi_2 \varepsilon_{t-2}^2 + ... + \phi_p \varepsilon_{t-p}^2 \qquad (2)$$

where ε_t^2 is the squared residuals, and LM test is performed by $LM = T * R^2$ (3)

T is the sample size

R^2 is derived from the Equation (2)

The volatility spillover effect from one market to direct property is examined by utilising a GARCH model, which was proposed by Bollerslev (1986). More specifically, LPTs, stocks and bonds were introduced into the conditional variance equation as exogenous variables. A GARCH (1, 1) model can be displayed as follows:

Mean Equation:

$$R_t = a_0 + a_1 R_{t-1} + a_2 R_{LPTs} + a_3 R_{Stocks} + a_4 R_{Bonds} + \mu_t \qquad (4)$$

where R_t is the return of direct property at the time t, μ_t is the residual, R_{LPTs} is the return of LPTs, R_{Stocks} is the return of stocks and R_{Bonds} is the return of bonds.

Variance Equation:

$$h_t^2 = \beta_0 + \beta_1 \mu_{t-1}^2 + \beta_2 h_{t-1}^2 + \beta_3 \mu_{LPTs}^2 + \beta_4 \mu_{Stocks}^2 + \beta_5 \mu_{Bonds}^2 \qquad (5)$$

[2] However, it is one of the limitations of this study that must be borne in mind.

where β_0 is the constant term of variance equation, μ_{t-1}^2 represents the lag of the squared residual from the mean equation (ARCH term), h_t^2 is the lagged h_t term (GARCH term), significant values of β_3, β_4 and β_5 indicate that current volatility in direct property is influenced by past volatility shocks in LPTs, stocks and bonds respectively.

One of the limitations of the GARCH model is it fails to consider the asymmetric issue in which it is not intuitively appealing to assume the model is symmetrically response to positive and negative shocks. Moreover, the asymmetric volatility is also demonstrated by Michayluk et al. (2006) in real estate, as well as in stocks, where this issue is extensively reviewed by Bekaert and Wu (2000)[3]. Thus, it is reasonable to expect that the response of direct property to negative shocks could be larger than positive shocks. Most importantly, numerous prior studies in stocks (Engle and Ng, 1993) and in REITs (Stevenson, 2002) have found evidence in favour of Exponential GARCH (EGARCH) where it exhibits more intuitively appealing results and performs surprisingly well.

In this respect, the EGARCH model is also employed in this study. As discussed by Nelson (1991), the EGARCH model allows for testing the asymmetric and volatility clustering simultaneously. The model of EGARCH (1,1) for direct property can be formulated as follows:

$$\log(h_t^2) = \beta_0 + \gamma_1 \left| \frac{\mu_{t-1}}{h_{t-1}} \right| + \gamma_2 \frac{\mu_{t-1}}{h_{t-1}} + \gamma_3 \log(h_{t-1}^2) + \gamma_4 \mu_{LPTs}^2 + \gamma_5 \mu_{Stocks}^2 + \gamma_6 \mu_{Bonds}^2 \tag{6}$$

where γ_2 examines leverage effect (asymmetric) in which if the asymmetric is presented, then the $\gamma_2 < 0$. Statistically significant values for γ_4, γ_5 and γ_6 suggest that past volatility shocks in LPTs, stocks and bonds influence current volatility in the direct property market.

The results obtained from the analyses are presented in the next section, showing whether there is evidence of volatility spillovers in direct property. The descriptive statistics for direct property, stocks, LPTs and bonds are outlined in Table 1.

[3] Although the explanations of asymmetric volatility (leverage effect and volatility feedback) have been discussed extensively in the finance literature, this is beyond the scope of this paper to examine the potential explanations of asymmetric volatility in the Australian direct commercial property market.

Table 1: Descriptive statistics

Asset	Direct property	Stocks	LPTs	Bonds
Mean	0.053	0.072	0.070	0.049
Median	0.048	0.088	0.061	0.045
Maximum	0.280	0.270	0.261	0.151
Minimum	-0.129	-0.240	-0.154	-0.084
Std. Dev.	0.071	0.103	0.079	0.045
Skewness	0.236	-0.524	-0.036	0.013
Kurtosis	4.959	3.478	3.776	3.653
Jarque-Bera	7.448**	2.431	1.112	0.782

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

As demonstrated in Table 1, the average return of stocks is 7.2% (the highest), while bonds offer the lowest return. The standard deviation of stocks is 10.3%, appearing as the highest level of risk, while bonds show the lowest risk level with 4.5%. Zero skewness is evident in LPTs and bonds, while other assets exhibit either an excess positive or negative skewness. Besides, leptokurtic is evident in all series. Both statistics indicate that return distribution for direct property are not normal. The Jarque-Bera statistics further reject the normal assumption in direct property. As stated by Bond and Patel (2003) and Najand et al. (2006), the non-normality evidence implies that the data of direct property is suitable to be analysed by using GARCH and ARCH.

Unit root tests were conducted with applying Augmented Dickey-Fuller and Phillips-Peron tests on all of the series. As highlighted by Cotter and Stevenson (2006), the purpose of these tests is to avoid misspecifications of the data and spurious conclusions. The unit root results are tabulated in Table 2.

Table 2: Unit root tests

Asset	Augmented Dickey-Fuller	Phillips-Peron
Direct Property	-7.101***	-4.198***
(ρ -value)	(0.000)	(0.010)
LPTs	-8.206***	-8.207***
(ρ -value)	(0.000)	(0.000)
Stocks	-5.241***	-6.520***
(ρ -value)	(0.001)	(0.000)
Bonds	-5.578	-7.057
(ρ -value)	(0.000)***	(0.000)***

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

Schwarz information criterion (SIC) is employed for selecting the optimal lag length. The Augmented Dickey-Fuller test (with a trend and an intercept) shows that all series are negative and statistically significant at 1%, indicating that these series are stationary. Consistently, Phillips-Peron test also provides similar results, confirming that the series are stationary and there is no unit root in the series. As a result, it is concluded that the returns of these series are stationary[4].

RESULTS AND DISCUSSION

The inter-asset correlation analysis is first undertaken in order to provide some preliminary indication of the linkages among these assets in this study. The correlation matrices between the different assets are displayed in Table 3.

Table 3: Inter-asset correlation matrix

	Direct property	stocks	LPTs	Bonds
Direct property	1.000			
Stocks	-0.053	1.000		
LPTs	-0.116	0.635	1.000	1.000
Bonds	-0.350	0.144	0.371	1.000

An immediate observation from the table is stocks and LPTs appear to be strongly correlated. In fact, the highest correlation is reported between these assets. Bonds are also moderately related to direct property. However, direct property is weakly correlated with LPTs, implying that direct property has very little connection to LPTs. The lowest correlation coefficient is also recorded between direct property and stocks. In other words, the influence of LPTs and stocks on direct property could be marginal. A weak correlation is also evident between bonds and stocks. In contrast, LPTs and bonds are moderate correlated with LPTs. Overall, direct property is weakly correlated in relation to stocks and LPTs, suggesting that diversification potential can be obtained by including these assets in a direct property portfolio. This also implies that the influence of stocks and LPTs on direct property is marginal. However, a more formal test, the GARCH/EGACRH model should be performed in order to verify it.

Volatility clustering

As discussed, the volatility clustering in direct property should be demonstrated before a GARCH model can be performed. Hence, the dependence in direct property return series is examined with using Ljung-Box tests and Engle (1982) LM test for ARCH for order of p . Table 4 reveals the results of Ljung-Box test and Engle (1982) LM test for ARCH.

[4] The stationary tests with a) a trend and b) neither a trend nor an intercept are also performed, no variation is found.

Table 4: Ljung-Box tests and ARCH test for direct property

ρ	**3**	**6**
Q(ρ)	8.098	14.954
	(0.044)**	(0.021)**
Q^2(ρ)	7.862	11.072
	(0.049)**	(0.086)*
ARCH(ρ)	7.655	28.330
	(0.054)*	(0.000)***

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

Obviously, there is little evidence to show that there is no ARCH effect for direct property in which the Ljung-Box statistics of squared returns are statistically significant at least at the 10% level. Similarly, the LM test for ARCH also confirms the presence of volatility clustering in the series where the LM statistics are statistically significant at least at 10%. Persistence in volatility is stronger with ARCH(6). The strong serial correlation suggests that the ARCH/GARCH effect is observed in direct property series. These indicate that the volatility of direct property is time-varying and occurs in clustering. These results are expected with regard to extensive previous studies have offered evidence of volatility clustering in the financial and housing markets. More importantly, these results support the application of GARCH model in which it appears as a preferable model for capturing the dynamics of returns and volatilities in the series.

Once the appropriateness of using GARCH/EGARCH models is demonstrated, the numbers of p and q for GARCH and EGARCH models are estimated. A comparison is also conducted by comparing the GARCH (1, 1) and EGARCH (1,1) with various higher-order GARCH(p , q) and EGARCH(p , q) specifications based on the SIC and Akaike Information Criteria (AIC). The results show that GARCH (1,1) and EGARCH (1,3) are the best specifications for both model respectively. Therefore, these model specifications are utilised in this study. The details of the specification selection results are exhibited in Appendix I.

Mean spillovers

Once the specification of the models are determined, the study employs GARCH (1,1) and EGARCH(1,3), as well as OLS to examine the explanatory power of LPTs, stocks and bonds on returns of direct property. Table 5 reports the results of mean equations[5].

[5] As this section is concerning with mean spillovers, only mean equations are reported.

Table 5: Mean spillovers

Models	OLS	GARCH(1,1)	EGARCH(1,3)
Panel A: LPTs			
Constant	0.039	0.033	0.034
	(1.670)	(17.559)***	(8.826)***
Lagged direct property	0.406	0.261	0.293
	(2.648)***	(3.861)***	(8.285)***
LPTs	-0.118	0.079	0.045
	(-0.675)	(1.107)	(1.228)
Panel B: Stocks			
Constant	0.034	0.027	0.022
	(1.483)	(4.862)***	(8.260)***
Lagged direct property	0.395	0.259	0.320
	(2.670)***	(4.796)***	(73.771)***
Stocks	-0.051	0.161	0.024
	(-0.327)	(2.190)**	(1.631)
Panel C: Bonds			
Constant	0.054	0.058	0.063
	(4.436)***	(4.742)***	(10.953)***
Lagged direct property	0.331	0.199	0.287
	(2.464)**	(1.705)*	(8.517)***
Bonds	-0.393	-0.431	-0.427
	(-2.345)**	(-3.520)***	(-8.430)***

Notes: This table reports estimated coefficients for mean equations and the corresponding t-statistics (in bracket). T-statistics of coefficients from OLS are adjusted to autocorrelation and heteroskedasticity according to Newey-West (1987). The mean model of GARCH (1,1) and EGARCH (1,3) are estimated by:
Mean Equation:

$$R_t = a_0 + a_1 R_{t-1} + a_2 R_{LPTs} + a_3 R_{Stocks} + a_4 R_{Bonds} + \mu_t$$

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

It is noticeable that an insignificant coefficient of LPTs is evident in the OLS, GARCH (1,1) and EGARCH(1,3) models, indicating that the LPT market has little predictive power to direct property. This is consistent with the findings from recent price discovery studies (Tuluca et al., 2000; Chau et al., 2001) in which indirect property fails to explain the variation in direct property returns. In other words, in terms of returns, indirect property (LPTs) conveys little information about direct property.

Similarly in Panel B, in a majority of cases, an insignificance coefficient of stocks is evident, showing that there is no strong evidence to show past stocks returns can explain direct property returns. The positive and statistical significant coefficient of stocks is only evident in the GARCH (1,1) model; no similar significant evidence is obtained from OLS and EGARCH(1,3) models. The results highlight the fact that investors have viewed property and stocks as different types of asset and acknowledge the fundamental difference among these assets.

On the other hand, in Panel C, all models exhibit a negative and statistically significant coefficient for bonds (Panel C), suggesting that past bond returns has significant negative impact on current direct property returns. The results reported here can be explained by the strong link between bonds and interest rates in which it is reasonable to expect that higher interest rate has a negative impact on direct property. In brief, it has shown that bonds have significant explanatory power to direct property returns, whereas no similar evidence is found for LPTs and Stocks.

It must also be noted that even though the un-smoothed process was undertaken into the direct property series, the coefficients for the lagged direct commercial property variables are significant, implying that the validity of this correction must be assessed. The Newell and MacFarlane (1995) correction method was also employed to examine the smoothing bias in the original direct property series. The results reveal that both methods have a quite similar annualised risk level for the Australian direct property series at around 9%-10% per annum. Importantly, the significance lagged return coefficients are also observed in the mean equation from the study of Wong et al. (2007) who employ transaction based data[6].

Volatility spillovers

Although the above section has demonstrated the linkages between direct property and LPTs, stocks and bonds, it is an analysis undertaken on the first-moment (returns). This section emphasises on the volatility linkages between direct property and these assets (second-moment). The results of volatility spillover are presented in Tables 6 and 7. Table 6 exhibits estimates for the conditional mean and conditional variance equations for direct property with using the GARCH (1,1) model.

[6] The author would like to thank the referee to highlight this point. The result of Newell and MacFarlane correction method is available from the author.

Table 6: Results of the GARCH(1,1) model with LPTs and stocks

Model	I	II	III
Panel A: Conditional mean equation			
Constant	0.034	0.044	0.036
	(2.904)***	(3.141)***	(4.924)***
Lag Return	0.415	0.301	0.287
	(3.048)***	(1.808)*	(2.168)**
Panel B: Conditional variance equation			
Constant	0.003	0.002	0.001
	(2.103)**	(2.705)***	(2.582)***
ARCH	0.072	0.200	0.007
	(0.449)	(1.469)	(0.083)
GARCH	0.482	0.645	1.008
	(1.544)	(5.090)***	(6.954)***
LPTs	-0.018		
	(-3.407)***		
Stocks		-0.014	
		(-2.567)**	
Bonds			-0.015
			(-2.146)**
$Q^2(3)$	5.431	4.250	1.039
	(0.143)	(0.236)	(0.792)
ARCH(3)	5.401	3.187	1.554
	(0.145)	(0.203)	(0.670)

Notes: This table reports estimated coefficients for mean and variance equations of GARCH (1,1) model. The model is estimated by

Mean Equation:

$$R_t = a_0 + a_1 R_{t-1} + \mu_t$$

Variance Equation:

$$h_t^2 = \beta_0 + \beta_1 \mu_{t-1}^2 + \beta_2 h_{t-1}^2 + \beta_3 \mu_{LPTs}^2 + \beta_4 \mu_{Stocks}^2 + \beta_5 \mu_{Bonds}^2$$

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

Panel A of Table 6 exhibits the results of mean equation in which the empirical results demonstrate that direct property can be explained by the lagged direct property returns. This is consistent with the results from Table 5. However, the focus of this study is concerned with the variance equation with regard to the volatility spillover effect.

Panel B of Table 6 reveals the results of variance equation. The results find that GARCH coefficients are statistically significant at the 1% level, the only exception is in Model I. However, no similar evidence is found for ARCH. These results are consistent with the results of Devaney (2001). Furthermore, the sum of the coefficients of ARCH and GARCH terms approaches 1 in Models II and III, indicating that the persistence in volatility shocks in direct property is quite strong.

A strong volatility spillover effect is also observed between LPTs and direct property in Model I. The coefficient of LPTs is significantly negative, suggesting that past volatility shocks LPTs have considerable negative influence on current volatility of direct property. In other words, the reaction of LPTs to the information or changes in volatility is quicker than direct property. This can be attributed the liquidity nature of LPTs in which investors in LPTs undoubtedly enjoy higher liquidity than direct property. More importantly, it refutes the recent findings in price discovery and implies that returns and volatility contain different set of information. This point has been demonstrated and discussed by Kallberg et al. (2003).

Besides, the negative and significance stock coefficient in Model II provides evidence of volatility spillover effect from stocks to direct property. In other words, the transmission of past volatility of stocks to current volatility of direct property is documented. This is inconsistent with the findings from mean equations. This further highlights the different between returns and volatility.

Similar strong spillover results are found in Model III in which the coefficient of bonds is negative and significant, signifying that the volatility of bonds has substantial contribution to direct property volatility. As discussed earlier, these results are intuitive in which higher bond returns (and/or interest rates) would lead some negative impacts on the direct property market. More importantly, the negative impacts of interest rates in the Australian commercial property market are also demonstrated in the next section.

Another important observation is that the GARCH (1,1) model appears as the model that is sufficient to remove any residual heteroskedasticity effects in light of insignificant LM statistics. Similar results are observed from the Ljung-Box test for autocorrelation of squared standardised residuals. This indicates that there is no sign of misspecification in the models and the serial dependence in the residual series for all series has been dramatically reduced by employing the GARCH (1,1) model.

The above analyses suggest that the volatility spillover effect is found between direct property and these capital assets by employing the GARCH (1,1) model. It should be noted that these models assume that assets are symmetric to positive and negative news. However, asymmetric is reasonable to be expected in direct property. In this regard, the EGARCH model is also utilised in this study.

The results of EGARCH (1,3) model are depicted in Table 7. Panel A of Table 7 reports the results of mean equations, which show that the return of direct property is statistically explained by its lag return at the 1% level in Models I, II and III. These results suggest that past returns have some explanatory power to current direct property returns.

Table 7: Results of the EGARCH(1,3) model with LPTs and stocks

Model	**1**	**2**	**3**
Panel A: Conditional mean equation			
Constant	0.0233	0.025	0.020
	(10.639)***	(11.913)***	(16.899)***
Lag Return	0.325	0.336	0.379
	(6.866)***	(93.443)***	(58.164)***
Panel B: Conditional variance equation			
Constant	-1.410	-13.091	-10.122
	(-3.269)***	(-7.741)***	(-19.517)***
|RES|/SQR[GARCH](1)	0.850	0.591	0.832
	(2.001)**	(1.037)	(2.660)***
|RES|/SQR[GARCH](2)	0.424	2.678	2.760
	(0.763)	(3.945)***	(5.129)***
|RES|/SQR[GARCH](3)	0.662	1.934	1.210
	(1.247)	(2.734)***	(3.394)***
RES/SQR[GARCH](1)	-1.231	-0.710	-1.095
	(-3.523)***	(-2.473)**	(-4.889)***
EGARCH(1)	0.919	-0.294	0.042
	(14.384)***	(-1.362)	(0.643)
LPTs	-10.147		
	(-4.314)***		
Stocks		2.560	
		(1.047)	
Bonds			-6.500
			(-9.233)***
$Q^2(3)$	0.583	3.980	4.439
	(0.900)	(0.264)	(0.218)
ARCH(3)	0.113	3.893	4.077
	(0.990)	(0.273)	(0.253)

Notes: This table reports estimated coefficients for mean and variance equations of EGARCH (1,3) model. The model is estimated by

Mean Equation:

$$R_t = a_0 + a_1 R_{t-1} + \mu_t$$

Variance Equation:

$$\log(h_t^2) = \beta_0 + \sum_{j=1}^{q} \chi_j \left| \frac{\mu_{t-j}}{h_{t-j}} \right| + \gamma_2 \frac{\mu_{t-1}}{h_{t-1}} + \gamma_3 \log(h_{t-1}^2) + \gamma_4 \mu_{LPTs}^2 + \gamma_5 \mu_{Stocks}^2 + \gamma_6 \mu_{Bonds}^2$$

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

On the variance dimension, a negative and significant effect emerges for LPTs. Specifically, Model I shows a negative and statistically significant coefficient of LPTs, suggesting that strong volatility spillover effect in volatility is found in the model. This provides further support to the results from Table 6, indicating that past volatility of LPTs has a negative impact on current volatility of direct property.

Model II investigates the volatility spillover of stocks to direct property with the EGARCH (1, 3) model. A positive and statistical insignificant coefficient of stock is evident, showing that no evidence of volatility transmission from stocks to direct property. However, these results are inconsistent with the results of Table 6. Different specifications of these models could be the possible explanation for this divergence. The divergence results from both specifications are also observed by Stevenson (2002). The volatility spillover evidence is also found in bonds in which a negative and statistically significant at 1% coefficient is evident. This means that past volatility of bonds determines current volatility of direct property. These results are consistent with the results in Table 6 for bonds.

Another important finding is that direct property is asymmetry in the news, where the γ_2 s (RES/SQR[GARCH(1)]) are negative and statistically significant at least at the 5% level, reflecting that the models are asymmetric responses to negative and positive shocks, and the variance increases more after negative shocks than positive shocks. This result is consistent with previous studies in international real estate markets such as Liow et al. (2005) and Michayluk et al. (2006). In addition, the diagnostic test results seem to strongly support the specification of the EGARCH (1,3) model. The LM statistics for ARCH are significantly less than the 10% critical value. Moreover, Ljung-Box statistics are also statistically insignificant, thus favouring the EGARCH(1,3) specification.

Overall, strong volatility spillover effects of LPTs and bonds on direct property have been documented in Tables 6 and 7, whereas mixed evidence is found in the stock market with utilising GARCH(1,1) and EGARCH(1,3) models. Furthermore, the insignificant statistics of LM and Ljung-Box tests indicate that both models are sufficient representations.

Robustness checks

To shed more light on the volatility spillover between direct property and capital assets, the baseline results are further controlled by including interest rate and inflation in the mean equation in respect to both factors have been viewed as the important factors in explaining direct property returns (Wong et al., 2006).

Table 8: The GARCH (1,1) model by controlling with interest rate and inflation in mean specification

Model	I	II	III	IV	V	VII
Panel A: Conditional mean equation						
Constant	0.031	0.047	0.041	0.047	0.061	0.069
	(1.807)*	(3.157)***	(3.305)***	(2.226)**	(2.295)**	(3.546)***
Lag	0.407	0.287	0.287	0.424	0.354	0.261
Return	(2.321)**	(1.781)*	(2.312)**	(4.292)***	(2.103)**	(1.878)*
Inflation	0.199	-0.048	-0.538			
	(0.271)	(-0.066)	(-0.777)			
Interest				-0.371	-0.698	-1.209
Rate				(-0.823)	(-0.946)	(-2.055)**
Panel B: Conditional variance equation						
Constant	0.003	0.001	0.001	0.003	0.001	0.001
	(1.889)*	(1.911)*	(2.848)***	(2.212)**	(1.306)	(2.323)**
ARCH	0.072	0.168	0.008	0.076	0.154	0.009
	(0.465)	(1.382)	(0.097)	(0.543)	(0.949)	(0.256)
GARCH	0.486	0.657	0.968	0.476	0.713	0.922
	(1.331)	(5.152)***	(6.887)***	(1.332)	(4.450)***	(24.172)***
LPTs	-0.019			-0.017		
	(-3.249)***			(-1.792)*		
Stocks		-0.012			-0.010	
		(-1.890)*			(-1.444)	
Bonds			-0.012			-0.011
			(-2.368)**			(-2.081)**

Notes: This table reports estimated coefficients for mean and variance equations of GARCH (1,1) by controlling interest rate and inflation. The model is estimated by

Mean Equation:

$$R_t = a_0 + a_1 R_{t-1} + a_5 Inflation + a_6 InterestRate + \mu_t$$

Variance Equation:

$$h_t^2 = \beta_0 + \beta_1 \mu_{t-1}^2 + \beta_2 h_{t-1}^2 + \beta_3 \mu_{LPTs}^2 + \beta_4 \mu_{Stocks}^2 + \beta_5 \mu_{Bonds}^2$$

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

Panel A of Table 8 shows that interest rate and inflation are insignificant in explaining the returns of direct property. The relevant mean spillover coefficients from GARCH models, in general, are negative and statistically insignificant. The mean spillover coefficients indicate that interest rate and inflation have little effect on direct property returns in Australia.

Turning our attention to variance equations in Panel B of Table 8 (the main focus of this section), no significant variation is observed by comparing these results and the baseline results in Table 6. Strong volatility spillover is found between direct property and these capital assets. The only exception is stocks in Model V. This indicates that the volatility spillover effect of LPTs and bonds to direct property is significant.

Table 9: The EGARCH(1,3) model by controlling with interest rate and inflation in mean specification

Model	I	II	III	IV	V	VII
Panel A: Mean equation						
Constant	0.041	0.023	0.018	0.037	0.036	0.027
	(6.463)***	(7.570)***	(4.386)***	(4.751)***	(8.342)***	(7.014)***
Lag Return	0.226	0.345	0.536	0.185	0.335	0.427
	(1.655)*	(25.977)***	(7.981)***	(1.592)	(47.610)***	(11.330)***
Inflation	0.220	-0.060	-0.530			
	(0.545)	(-0.244)	(-6.994)***			
Interest Rate				0.318	-0.418	-0.422
				(1.132)	(-3.779)***	(-10.818)***
Panel B: Variance equation						
Constant	-1.860	-10.385	-8.848	-2.286	-9.127	-11.540
	(-1.271)	(-2.981)***	(-3.832)***	(-1.298)	(-7.644)***	(-10.241)***
|RES|/SQR	1.156	0.407	0.866	1.088	0.095	0.653
[GARCH](1)	(1.736)*	(0.480)	(1.897)*	(1.594)	(0.191)	(1.359)
|RES|/SQR	0.668	3.588	1.555	0.054	3.205	0.257
[GARCH](2)	(1.110)	(2.916)***	(3.517)***	(0.914)	(4.296)***	(0.432)
|RES|/SQR	0.568	1.856	2.083	0.762	1.181	1.603
[GARCH](3)	(0.849)	(1.179)	(3.310)***	(1.047)	(1.014)	(1.991)**
RES/SQR	-0.856	-0.909	-1.226	-0.746	-1.146	-0.630
[GARCH](1)	(-1.966)**	(-1.762)*	(-3.121)***	(-1.815)*	(-3.863)***	(-2.122)**
EGARCH(1)	0.947	0.005	0.137	0.878	0.065	-0.685
	(3.449)***	(0.011)	(0.508)	(2.885)***	(0.914)	(-9.375)***
LPTs	-7.635			-7.964		
	(-2.606)***			(-2.592)***		
Stocks		2.469			1.943	
		(1.007)			(0.738)	
Bonds			-12.134			-14.041
			(-2.856)***			(-3.425)***

Notes: This table reports estimated coefficients for mean and variance equations of EGARCH (1,3) by controlling interest rate and inflation.
Mean Equation:

$$R_t = a_0 + a_1 R_{t-1} + a_5 Inflation + a_6 InterestRate + \mu_t$$

Variance Equation:

$$\log(h_t^2) = \beta_0 + \sum_{j=1}^{q} \chi_j \left| \frac{\mu_{t-j}}{h_{t-j}} \right| + \gamma_2 \frac{\mu_{t-1}}{h_{t-1}} + \gamma_3 \log(h_{t-1}^2) + \gamma_4 \mu_{LPTs}^2 + \gamma_5 \mu_{Stocks}^2 + \gamma_6 \mu_{Bonds}^2$$

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

Table 9 exhibits the results of EGARCH (1, 3) model once the interest rate and inflation are controlled in mean equations. Interestingly, in contrast to Table 8, the interest rate appears as a significant factor to explain returns, although inflation reveals some contrary results.

Consistent to Tables 7 and 8, a significant negative effect of past LPT and bond volatilities on current direct property volatilities is evident in Table 9 in which Panel B of Table 9 confirms the strong negative influence from the volatility shocks of LPTs and bonds to direct property. This indicates that direct property is strongly linked to LPTs and bonds. Nevertheless, no obvious spillover effect is evident in stocks. This presents evidence of no significant discrepancy is found by controlling the models with interest rate and inflation variables in mean equations.

These results are consistent to the results of Alonso and Blanco (2005) in which variance equations in GARCH and EGARCH models are fairly robust to alternative mean specifications with little variation in the variance equation is observed. In summary, the baseline results are robust to the inclusion of additional variables in mean equations. Clear volatility spillover evidence of LPTs and bonds to direct property is also confirmed.

PROPERTY INVESTMENT IMPLICATIONS AND CONCLUSIONS

Extensive empirical studies have shown the return linkages between direct property and capital assets. However, there have been little real estate studies on the relationships among these assets in relation to volatility. Hence, this paper examines the linkages among direct property and LPTs, stocks and bonds from the volatility perspective.

Several important findings have been found in this study. Firstly, there is evidence of volatility clustering in direct property series. This shows that direct property is consistent with the financial time series data in which the volatility of direct property is time-varying and clustering. This suggests that standard mean-variance analysis could fail to characterise this time-variation by assuming variance is constant. More importantly, during volatile periods, the standard mean-variance analysis might underestimate the risk level of an asset than it should be. Secondly, LPTs and bonds would appear to be influential in affecting the direct property volatility; there is strong evidence of significant spillover from LPTs and bonds to direct property. In other words, the volatilities of LPTs and bonds would be transmitted to direct property. Mixed-results are reported for stocks. Thirdly, direct property is asymmetric to bad and good news. More specifically, the results show that direct property is more sensitive to negative shocks than positive shocks. Finally, the first-moment and second-moment might contain different set of information in which no significant evidence is available to show that LPTs can explain returns of direct property, although this is contrast to the results from volatility spillover. All of these findings provide additional insights into the risk profiles of direct property.

Additionally, these findings have some important property investment implications, such as real estate portfolio management and risk management. It would appear that utilising GARCH and EGARCH models are crucial for fund managers to manage the risk in their direct property investments in respect to volatility clustering is documented in direct property. Since it has also shown that a shock, particularly a negative shock, in LPTs and bonds would be transmitted to direct property, fund managers should adjust their portfolio allocations accordingly to volatility movements in LPTs and bonds. Besides, the findings also suggest that investors and fund managers should not only focus on the first-moment (returns), the second-moment (volatility) could also contain different vital information. The findings have also provided a better understanding for investors in direct property investment.

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Appendix I: Specification selection SIC and AIC comparison

Models	SIC	AIC
Panel A: GARCH		
(1,1)	**-2.661 (1)**	-2.866 (2)
(1,2)	-2.613 (2)	-2.859 (3)
(1,3)	-2.552 (5)	-2.838 (4)
(2,1)	-2.559 (4)	-2.805 (6)
(2,2)	-2.533 (6)	-2.820 (5)
(2,3)	-2.478 (7)	-2.805 (6)
(3,1)	-2.600 (3)	**-2.887 (1)**
(3,2)	-2.439 (8)	-2.767 (8)
(3,3)	-2.384 (9)	-2.753 (9)
Panel B: EGARCH		
(1,1)	-2.686 (8)	-2.441 (6)
(1,2)	-2.765 (6)	-2.479 (4)
(1,3)	**-2.973 (1)**	**-2.646 (1)**
(2,1)	-2.575 (9)	-2.288 (9)
(2,2)	-2.791 (4)	-2.463 (5)
(2,3)	-2.935 (2)	-2.566 (2)
(3,1)	-2.765 (6)	-2.437 (7)
(3,2)	-2.780 (5)	-2.411 (8)
(3,3)	-2.903 (3)	-2.493 (3)

Notes: Bracket ( ) indicates the ranking

Interestingly, Panel A shows that the GARCH (1,1) specification is the best model based on the SIC, whereas the AIC reveals that the GARCH(3,1) model is the best fitted model and the GARCH(1,1) model is ranked as the second well-fitted model. Since extensive studies in the finance (Bollerslev *et al.*, 1992) and real estate literature (Wong *et al.*, 2006) have confirmed the GARCH (1, 1) model is the most convenient and appropriate specification, the GARCH(1,1) model is employed in this study. On the other hand, the results in Panel B illustrate that the EGARCH (1,3) model specification is the best-fitted EGARCH specification based on both SIC and AIC criteria. Thus, the EGARCH (1, 3) model is the preferable specification and it is employed in this study. In short, GARCH (1, 1) and EGARCH(1,3) specifications are utilised in this study.

INTERNATIONAL PROPERTY RESEARCH CONFERENCE: UPDATE

Several international property conferences will be held in different parts of the world in 2009. These include:

- **PACIFIC RIM REAL ESTATE SOCIETY CONFERENCE**
  Sydney, Australia: January 2009

- **AMERICAN REAL ESTATE SOCIETY CONFERENCE**
  Monterey, USA: April 2009

- **EUROPEAN REAL ESTATE SOCIETY CONFERENCE**
  Stockholm, Sweden: June 2009

- **ASIAN REAL ESTATE SOCIETY CONFERENCE**
  Los Angeles, USA: July 2009

PRRES members are welcome to participate in these major property conferences. Check the websites of the respective real estate societies for further details regarding these conferences.