Macroeconomic risk factors in Australian commercial real estate, listed property trust and property sector stock returns: A comparative analysis using GARCH-M

TRACEY WEST

School of Economics and Finance, Queensland University of Technology, Brisbane, Queensland 4001, Australia

ANDREW C. WORTHINGTON

School of Accounting and Finance, University of Wollongong, Wollongong, New South Wales 2522, Australia

Summary

This paper employs a Generalised Autoregressive Conditional Heteroskedasticity in Mean (GARCH-M) model to consider the effect of macroeconomic factors on Australian property returns over the period 1985 to 2002. Three direct (office, retail and industrial property) and two indirect (listed property trust and property stock) returns are included in the analysis, along with market returns, short, medium and long-term interest rates, expected and unexpected inflation, construction activity and industrial employment and production. In general, macroeconomic factors are found to be significant risk factors in Australian commercial property returns. However, the results also indicate that forecast accuracy in these models is higher for direct office, listed property trust and property stock returns and that the persistence of volatility shocks varies across the different markets, with volatility half lives of between five and seven months for direct retail and industrial property, two and three months for direct office property and less than two months with both forms of indirect property investment.

***Keywords*:** Property returns; listed property trust, property stocks, market risk; interest rate risk; industrial production and construction activity, generalised autoregressive conditional heteroskedasticity in mean (GARCH-M) models

Introduction

The turn of the century witnessed a surge in Australia's property market performance, with personal investors, developers and fund managers alike 'rediscovering' the property market after the economic recession of the early 1990s. While some of the attention may be attributed to portfolio reallocation associated with the prolonged equity bear market and the subsequent redirection of capital, it is clear that Australia's economic conditions have combined together to provide an environment favourable to property investment. Low and stable interest and inflation rates, strong and sustained growth in residential and commercial property prices, long-lasting trends towards inner-city, high-density and coastal living, financial deregulation combined with intense competition and the development of new loan products with tax

advantages are just some of the factors associated with this renewed interest in Australian property investment.

Much theoretical and empirical work already exists focusing on the link between property (or real estate) returns and macroeconomic variables [see, for instance, Kling and McCue (1987), McWilliams (1992), McCue and Kling (1994), Liow (1997) and Brooks and Tsolacos (1999)]. Such information is demonstrably valuable in providing an improved understanding of property investment risk factors and yielding better and more accurate forecasts of future property returns, especially when "…considerable evidence indicates that state variables such as the slope of the term structure, expected and unexpected inflation, industrial production, and the spread between high-grade and low-grade bonds proxy for economic risk factors that are rewarded, *ex ante*, in the stock market" (Ling and Naranjo 1997, p. 284).

Interest rates and interest rate spreads, for instance, are considered good indicators of economic activity and are therefore posited to contain information about property return movements. "The main reason for this link is the assumption that returns relate directly to the present and future state of the economy and business conditions, and these are in part governed by interest rates" (Brooks and Tsolacos 2001, p. 711). Several empirical studies have already found that interest rates help explain a significant proportion of the variability in property returns [see, for example, Chen et al. (1986), Chan et al. (1990), McCue and Kling (1994), Liow (2000), Brooks and Tsolacos (2001) and Liow et al. (2003)].

Similarly, property investment is often regarded as an inflation hedge and the relationship between inflation and property returns is a recurrent theme in the literature [see, amongst others, Hoesli (1994), Liu et al. (1997), Bond and Seiler (1998), Quan and Titman (1999), Stevenson and Murray (1999) and Onder (2000)]. Bond and Seiler (1998, p. 327) have justified this interest on the basis that "…financial assets, such as common stocks and bonds, have been found to be poor performers when inflation is higher than expected. Therefore if real estate is an effective hedge against expected inflation, then it should likely be included in efficient portfolios".

Finally, property returns are also likely to be influenced by other demand and supply-side factors that can be easily measured at the macro level. Employment growth in particular industries, for example, may signal superior property returns through the flow through of increased demand for commercial space to rental rates and valuations (Liang and McIntosh, 1998). The contention that macro demand and supply conditions influence property returns has also been addressed by focussing on its link with construction activity (Eppli et al. 1998), industrial production (Karolyi and Sanders 1998), stock markets (Quan and Titman 1997,

1999; Lizieri and Satchell 1997), aggregate consumption (Ling and Naranjo 1997, 1998; Crone and Voith, 1999) and monetary policy (Johnson and Jenson 1999).

However, examination of the existing empirical literature concerning the relationships between macroeconomic variables and property markets reveals a number of shortcomings. First, many studies in the past have focused on the analysis of a single macroeconomic factor. Of these, the larger number have been concerned with interest rates or inflation rates and few have concerned themselves with a broader examination of the role of several macroeconomic variables in the return generation process [see, for instance, Chan et al. (1990), McCue and Kling (1994), Bond and Seiler (1998), Quan and Titman (1999), Onder (2000), Brooks and Tsolacos (2001) and Liow et al. (2003)]. Importantly, while interest and inflation rates are accepted as primary influences on property returns, a wider set of macroeconomic variables are normally employed in studying risk factors in the returns of financial assets, including stocks and bonds (Ling and Naranjo 1997).

Second, with few exceptions these studies have been conducted in the United States. While some recent work has been placed in the United Kingdom (Brooks and Tsolacos 2001), Singapore (Liow 2000; Liow et al. 2003), Turkey (Onder 2000) and Ireland (Stevenson and Murray 1999), only a single contribution (Okunev et al. 2002) is known in the Australian context. "Since the bulk of relevant research has been undertaken in the US, similar studies in other macroeconomic and property market environments are expected to generate useful comparative evidence" (Brooks and Tsolacos 1999, p. 141).

Third, nearly all studies have examined direct and indirect (or listed) property returns in isolation [see Quan and Titman (1999), Stevenson and Murray (1999) and Liow (2000) in the first instance and Liu and Mei (1992), McCue and Kling (1994) and Liu et al. (1997) in the second]. While direct and listed property has the same underlying asset base, they have different characteristics and can perform quite differently (Stringer 2001). Direct property values, for example, are based on appraised valuations while listed property is priced daily to market. Consequently, direct property returns are often less volatile than listed property returns since the appraisal-based valuations have a smoothing effect. Similarly, the standardised nature of listed property implies differences in the liquidity premium required by investors while corporate governance requirements in stock markets imply the timely and complete disclosure of information. Lastly, it is recognised that direct property returns are highly correlated with the changing demand fundamentals in the economic cycle, while listed property returns are more closely aligned with changes in the liquidity cycle, reflecting the conduct of monetary policy (Stringer 2001).

Finally, the manner in which market shocks are transmitted across time arouses interest in modelling the dynamics of the property return generation process. This calls for the application of autoregressive conditional heteroskedasticity (ARCH) models that take into account the time-varying variances of time series data, given it is suggested that property risk factors sensitivities and return premia vary temporally [see, for example, Ling and Naranjo (1997)]. Although ARCH methodology has been used extensively in modelling financial time series, to the authors' knowledge a detailed study of the application of ARCH to property markets has not been undertaken. Since ARCH models are specifically designed to allow risk to vary over time they provide a more theoretically sound framework with empirically more efficient estimators and more accurate forecasts of returns than those that have been conventionally employed in this literature.

In this paper an attempt is made to examine the impact of macroeconomic risk factors on the property return generation process in Australia using an ARCH methodology. The information used for this purpose includes both direct appraisal-based and indirect stock market-based returns. The remainder of the paper is divided into four main areas. The second section provides a description of the data employed in the analysis. The third section discusses the empirical methodology used. The results are dealt with in the fourth section. The paper ends with some concluding remarks in the final section.

Description and properties of the data

The sample period for the analysis is March 1985 to December 2002. This is the longest and most recent period where consistent macroeconomic and property market data are available. The property market data employed in the study are monthly indices for five Australian property portfolios. The first set is direct commercial property indices obtained from the *Australian Property Council*. Bruggeman et al. (1984), Hoesli (1994), Quan and Titman (1999), Stevenson and Murray (1999) and Liow (1999) also specified direct property indices in their respective analyses of macroeconomic risk factors in property returns. These measures are appraisal-based accumulation indexes that are used to measure total returns from office, retail and industrial property in Australia by tracking over 70 percent of all properties held in institutional portfolios. An 'Office' (*OFF*) index covers office properties held in institutional portfolios for the capital cities of Sydney, Melbourne, Brisbane, Canberra, Adelaide and Perth; a 'Retail' (*RET*) index includes Australian shopping centres classified as major

regional, super regional, regional, sub regional and neighbourhood; and an 'Industrial' (*IND*) index incorporates the major industrial areas of Sydney, Brisbane and Melbourne.

The second set of indices relates to indirect (or listed) commercial property returns from the *Australian Stock Exchange*. The use of listed property trusts (equivalent to real estate investment trusts in the United States) and property stocks as indicators of property market performance follows the work of McCue and Kling (1994) and Karolyi and Sanders (1998), amongst others. The ASX/LPT 300 Index provides *Australian Stock Exchange* information for listed property trusts (*LPT*) while the property sector index (*STK*) is used for property sector stocks. Both indexes are obtained from *Datastream*. The natural log of the relative price for each of the five indexes is computed at monthly intervals to produce a time series of continuously compounded monthly returns, such that $r_t = \log(p_t/p_{t-1})$, where p_t and p_{t-1} represent the index price at time t and t-1, respectively. At high sampling frequencies (i.e. daily) the difference between discrete $[r_t = (p_t - p_{t-1})/ p_{t-1}]$ and continuously compounded returns is small; at low frequencies (i.e. monthly) the continuously compounded return is recognised as providing a better indication of real world income reinvestment.

The remaining variables specified are macroeconomic indicators used to explore the sensitivity of property returns to exogenous macroeconomic factors including market returns, interest rates, expected and unexpected inflation rates, and supply and demand-side variables such as construction activity, industrial production and employment. First, the *Australian Stock Exchange* All Ordinaries Accumulation Index as the market portfolio benchmark for Australian equity investors is used to calculate market returns (*MKT*). By way of comparison, Liow et al. (2003) used the Singapore All-share index as the market portfolio in their study of the interest rate sensitivity of Singaporean property stocks, Stevenson and Murray (1999) specified the market wide ISEQ Index for Irish property returns, while Ling and Naranjo (1997) employed a value-weighted portfolio of NYSE, AMEX and NASDAQ stocks in their analysis of macroeconomic risk factors in US property returns. Information on the market portfolio is also obtained from *Datastream.* Second, short, medium and long-term interest rates are proxied by the *Reserve Bank of Australia's* 90-day Bank-Accepted Bill (*SBD*), 5-year Commonwealth Bond (*MBD*) and 10-year Commonwealth Bond (*LBD*) price indexes. This parallels Brooks and Tsolacos (2001) who used the 3-month Treasury bill and 20-year gilt bond rate to proxy short and long-term interest rates in the United Kingdom, but differs from Ling and Naranjo (1997) who employed the difference between the US Treasury's 3-month bill and 10-year bond rates.

Third, the *Australian Bureau of Statistic's* Consumer Price Index for the housing sector is used to provide two measures of inflation. Following Karolyi and Sanders (1998) the index is decomposed into expected (*EIN*) and unexpected inflation (*UIN*) by applying the Box-Jenkins autoregressive integrated moving average (ARIMA) model to the consumer price index, with expected inflation measured as the forecast of the regression and unexpected inflation as the residual. Ling and Naranjo (1997), Liu et al. (1997) and Onder (2000) also specified inflation in terms of its expected and unexpected components.

The other variables are also sourced from the *Australian Bureau of Statistics*. Construction activity (*CNS*) is proxied by the 'number of building approvals for non-residential building', and is an indicator of the supply-side response to demand pressures in the market while 'industrial production (*INP*) is proxied by the articles produced indices for manufacturing, and represents the market demand for property assets. Finally, the following employment indexes by industry classification are used to proxy additional demand factors for property assets: namely, Mining (*MIN*), Manufacturing (*MAN*), Electricity, Gas, Water Supply and Communications (*ECO*), Construction (*CON*), Wholesale and Retail Trade (*WRT*), Accommodation, Cafés, Restaurants, Cultural and Recreational Services (*ARC*), Transport and Storage (*TRN*), Finance and Insurance (*FIN*), Property and Business Services (*SER*), and Government Administration and Defence (*GOV*). By comparison, Liang and MacIntosh (1998) also included employment effects in their studies, though with a non-farm employment growth index. All macroeconomic indexes are converted to a series of monthly changes to provide consistency with the calculation of the property returns.

Table 1 presents the summary of descriptive statistics of the monthly returns for the five property portfolios: namely, direct office (*OFF*), retail (*RET*) and industrial (*IND*) returns and indirect listed property trust (*LPT*) and property stock (*STK*) returns. Sample means, medians, maximums, minimums, standard deviations, skewness, kurtosis and the Jacque-Bera statistic and first-order autocorrelation coefficient and their *p*-values are reported. The lowest mean returns over the period were for *STK* (0.0101) and *OFF* (0.0202) and highest mean returns are for *RET* (0.0308) and *LPT* (0.0291). The largest and smallest monthly returns are both for *STK* (0.1971 and -0.3358, respectively). As shown, the standard deviations of returns range from 0.0.0127 (*RET*) to 0.0671 (*STK*). On this basis, of the market measures *RET* and *IND* are the least volatile, with *LPT* and *STK* being the most volatile. Table 1 also includes descriptive statistics for the continuously compounded changes in the macroeconomic variables. As shown, monthly changes in interest rates (*SBD*, *MBD* and *LBD*) were on average negative during this fifteen year period, along with unexpected inflation (*UIN*) and employment in the

mining (*MNG*), manufacturing (*MAN*) and electricity, gas, water supply and communications (*ECO*) industries. The most volatile macroeconomic variables (as measured by standard deviation) were construction activity (*CNS*), short (*SBD*), medium (*MBD*) and long-term (*LBD*) interest rates and market returns (*MKT*).

<TABLE 1 HERE>

By and large, the distributional properties of the property return series (*OFF*, *RET*, *IND*, *LPT*, *STK*) along with the equity market (*MKT*) appear non-normal. Three of the return series are significantly negatively skewed, ranging from -1.4901 (*IND*) to -2.4779 (*MKT*), indicating the greater probability of large deceases in returns than increases. The returns for retail property (*RET*) are positively skewed, also suggestive of volatility clustering in monthly property returns. None of the macroeconomic changes are significantly skewed. The kurtosis, or degree of excess, in all of the return series is also large, ranging from 3.2055 for *LPT* to 16.6139 for *MKT*, thereby indicating leptokurtic or fat-tailed distributions. The kurtoses for the macroeconomic series are also all significant, though less than three, thereby indicating platykurtic distributions.

The calculated Jarque-Bera statistics and corresponding *p*-values in Table 1 are used to test the null hypotheses that the distribution of the returns and macroeconomic series is normally distributed. The *p*-values for *RET*, *IND*, *STK*, *MKT*, *UIN*, and *CST* are smaller than the .05 level of significance suggesting the null hypothesis can be rejected. These series are then not well approximated by the normal distribution. To test for the presence of autocorrelation in each series, the first order autocorrelation coefficients are also calculated and presented in Table 1 along with their corresponding *p*-values. On this basis, first-order autocorrelation is evident in all the return series at the .10 level or higher, with positive autocorrelation (or persistence) in *OFF*, *RET*, *IND* and *LPT* and negative autocorrelation (or mean reversion) in *STK* and *MKT*. Of the macroeconomic variables *SBD*, *EIN*, *CNS*, *INP*, *ECO* and *TRN* exhibit significant first-order autocorrelation, with short-term interest rates (*SBD*), expected inflation (*EIN*) and industrial production (*INP*) being positive

Model specification

The distributional properties of Australian property returns indicate that generalized autoregressive conditional heteroskedastistic (GARCH) models can be used to examine the dynamics of the return generation process. Autoregressive conditional heteroscedasticity (ARCH) models and generalised ARCH (GARCH) models that take into account the time-

varying variances of time series data have already been widely employed. Suitable surveys of ARCH modeling in general and/or its widespread use in finance applications may be found in Bera and Higgins (1993) and Bollerslev et al. (1994). Pagan (1996) also contains discussion of developments in this ever-expanding literature.

The specific GARCH(p,q)-M model used in the present analysis is considered appropriate for several reasons. First, the capital asset pricing model (CAPM) and the arbitrage pricing theory (APT) establish the well-known (positive) relationship between asset risk and return. At a theoretical level, asset risk in both CAPM and APT is measured by the conditional covariance of returns with the market or the conditional variance of returns. ARCH models are specifically designed to model and forecast conditional variances and by allowing risk to vary over time provide more efficient estimators and more accurate forecasts of returns than those conventionally used to model conditional means.

Second, an approach incorporating GARCH(p,q) can quantify both long and short-term memory in returns. While ARCH allows for a limited number of lags in deriving the conditional variance, and as such is considered to be a short-term memory model, GARCH allows all lags to exert an influence and thereby constitutes a longer-term memory model. This reflects an important and well-founded characteristic of asset returns in the tendency for volatility clustering to be found, such that large changes in returns are often followed by other large changes, and small changes in returns are often followed by yet more small changes. The implication of such volatility clustering is that volatility shocks today will influence the expectation of volatility many periods in the future and GARCH(p,q) measures this degree of continuity or persistence in volatility.

Finally, the GARCH in mean (GARCH-M) model is very often used in financial applications where the expected return on an asset is directly related to the expected asset risk such that the estimated coefficient on risk is a measure of the risk-return trade-off. In these models the mean of the return series is specified as an explicit function of the conditional variance of the process, allowing for both the fundamental trade-off between expected returns and volatility while capturing the dynamic pattern of the changing risk premium over time.

Such model assumptions are generally consistent with Australian property market behaviour. Certainly property investors are not indifferent to the volatility of the investments they hold - as uncertainty in return varies, so does the risk premium required by investors. Moreover, property return volatility has varied widely during this period and high leverage in property investment makes investors particularly sensitive to these changes. In addition, these assumptions directly link the volatility clustering observed in property markets with two

pertinent explanations. To start with, the irregular news arrival process can at least, in part, explain volatility clustering, even when the market incorporates such information perfectly and immediately. At the macro level nominal interest rates, business cycles, industrial production and other indicators have already been proposed as sources of this clustering. However, it is also the case that if market participants have heterogenous beliefs and there are lags in the absorption of information, volatility clustering may also occur. This appears especially likely in property markets since they are conventionally regarded as being less homogenous and informationally efficient than their financial counterparts.

The GARCH(p,q)-M model used is described by the following:

$$r_{s,t} = \alpha_{s,0} + \alpha_{s,k} \sum_{k=1}^{n} x_{s,k} + \gamma_{s,0} h_{s,t} + \varepsilon_{s,t} \tag{1}$$

$$h_{s,t} = \beta_{s,0} + \beta_{s,i} \sum_{i=1}^{p} \varepsilon_{s,t-i}^{2} + \gamma_{s,j} \sum_{j=1}^{q} h_{s,t-j} \tag{2}$$

$$\varepsilon_{s,t} \left| \Omega_{s,t-1} \right. \sim N\left(0, h_{s,t}\right) \tag{3}$$

where the variables in the mean equation (1) are as follows: $r_{s,t}$ is the return on the sth property portfolio at time t (where s = *OFF, RET, IND, LPT* and *STK*), $x_{s,k}$ are the set of k macroeconomic factors expected to influence $r_{s,t}$ (where x = *MKT*, *SBD*, *MBD*, *LBD*, *EIN, UIN, INP, MNG, MAN, ECO, CST, WRT, ARC, TRN, FIN, SER* and *GOV*), $h_{s,t}$ measures the return volatility or risk of property market portfolio s at time t, and $\varepsilon_{s,t}$ is the error term which is normally distributed with zero mean and a variance of $h_{s,t}$, as described by the distribution in (3). The sensitivity of property market portfolio s at t to the macroeconomic factors are measured by the n parameters of $\alpha_{s,k}$ while $\alpha_{s,0}$ is the constant term.

The conditional variance $h_{s,t}$ follows the process described in (2) and for the sth property portfolio is determined by the past squared error terms (ε^2_{t-1}) and past behaviour of the variance (h_{t-1}), $\beta s,_0$ is the time-invariant component of risk for the sth portfolio, $\beta s,_i$ are the ARCH parameter(s) and $\gamma_{s,j}$ are the GARCH parameter(s). The robustness of the model depends on the sum of the ARCH and GARCH parameters being less than unity ($\beta_{s,i} + \gamma_{s,j} < 1$) for all s. Heteroskedasticity consistent covariance matrices are estimated following the methods described by Bollerslev and Wooldridge (1992)

Empirical results

The estimated coefficients and standard errors for the conditional mean return and variance equations are presented in Table 2. Different GARCH(p,q) models were initially fitted to the

data and compared on the basis of the Akaike and Schwarz Information Criteria (results not shown) from which a GARCH(2,2) model was deemed most appropriate for modelling the monthly return process for the direct property returns (*OFF*, *RET* and *IND*) and a GARCH(1,1) model for the indirect property returns (*LPT* and *SEC*). By way of comparison, a GARCH(1,1) specification has generally been shown to be a parsimonious representation of conditional variance that adequately fits most financial time series.

A similar testing procedure was employed to test which of the three specifications for interest rates (short, medium or long-term) was econometrically most appropriate to the return generation process in each property market. On this basis, short term interest rates (*SBD*) were specified for *OFF* and *IND* and long-term rates (*LBD*) for *RET*, *LPT* and *STK*. The Lagrange multiplier tests for autoregressive conditional heteroskedasticity (ARCH) in the residuals in Table 3 fail to reject the null hypothesis of no ARCH effects in the lagged squared residuals in these models up to order twenty and we may conclude that the ARCH parameters are correctly specified. However, the *F*-statistic of the null hypothesis that all coefficients are jointly zero in Table 2 is not significant at any conventional level for the models employing direct retail (*RET*) and industrial (*IND*) property returns. We may then question the contribution of the macroeconomic variables included in the models in explaining the return generation process in these particular portfolios.

A basic hypothesis examined is whether volatility is a significant factor in property pricing, or equivalently, whether intertemporal tradeoffs exist between risk and return in property markets. As indicated by the significance of the estimated coefficient for the GARCH parameter in the mean equation, only in the case of direct office (*OFF*), listed property trust (*LPT*) and property stocks (*STK*) is it significant. Theory suggests that the equilibrium price of systematic risk should be significant and positive, but as a measure of total rather than non-diversifiable systematic risk an increase in volatility need not always be accompanied by an increase in the risk premium. This is the case with direct retail (*RET*) and industrial (*IND*) returns. This is especially so if fluctuations in volatility are mostly due to shocks to unsystematic, as against systematic, risk. The negative sign on the volatility parameter for listed property trusts and property company securities are thought to be reflective of their position in equity portfolios. If property securities are less strongly affected by random shocks than other sectors, investors will switch to property securities in response to these shocks, thereby resulting in a lower risk premium.

<TABLE 2 HERE>

Table 2 also includes the estimated coefficients, standard errors and *p*-values for the set of macroeconomic parameters included in the analysis. The significance, magnitude and sign on the estimated coefficients vary across the different types of property returns. Of the seventy-five slope coefficients estimated across the five property portfolios, thirty-five (47 percent) are significant at the .10 level or higher. Consider direct office returns (*OFF*). All other things being equal, short-term interest rates (*SBD*), expected (*EIN*) and unexpected (*UIN*) inflation, construction activity (*CNS*) and employment changes in the mining (*MNG*), manufacturing (*MAN*), energy, gas and water supply and communication (*ECO*), construction (*CST*), transport (*TRN*), finance and insurance services (*FIN*) and property and business services (*SER*) industries are positively associated with direct office returns, with employment in accommodation and recreational services (ACO) being negatively related. Alternatively, with property stocks (*STK*) the only significant risk factors are market returns (*MKT*), long-term interest rates (*LBD*) and employment in the energy, gas and water supply and communication (*ECO*), construction (*CNS*) and wholesale and retail trade (*WRT*) industries.

Wald tests of the joint significance of combinations of these variables are conducted and the results presented in Table 3. As indicated, inflation is a significant risk factor in all property markets save property company securities, production is significant in direct retail and industrial and listed property trust markets, and changes in industrial employment are significant in direct office, retail and industrial markets. Combined together, market returns and interest rates are the largest risk factors for listed property trust and property sector stocks; expected inflation and industrial production are the greatest risk factors for direct retail and industrial returns, while for direct office returns the most important factors are expected inflation and changes in employment in property and business services.

One interesting question is whether given the number of insignificant *p*-values some of the variables are correlated and could be combined using a proxy variable. In response, there are actually very few parameters in this model: the ten unique industry dummy variables, for instance, could not be combined in any meaningful way. Moreover, while model refinement can sensibly take place with the different interest rate measures, which are invariably collinear, the remaining parameters represent unique macroeconomic influences. Lastly, since the primary emphasis in this paper is on forecasting ability, the presence of any collinear relationships, if any, is of somewhat lesser importance.

The lower portion of Table 2 presents the estimated coefficients for the conditional variance equations in the GARCH models. The constant term (*CON*) in the variance equation constitutes the time-independent component of volatility and reflects the volatility if no

ARCH (last period's shock) or GARCH (previous period's shocks) effect is significant. In the case of the models for *RET*, *IND* and *LPT* the estimated coefficient is significant and positive, though its magnitude is very small, suggesting all or nearly all volatility in property returns is made up of time-varying components. The own-innovation spillovers (ARCH) in all five returns are significant indicating the presence of strong ARCH effects, while the lagged volatility spillovers (GARCH) are always less significant as is their magnitude. This implies that the last period's volatility shocks in property returns have a greater effect on its future volatility than the memory of previous surprises.

<TABLE 3 HERE>

The sum of the ARCH and GARCH coefficients measures the overall persistence in each market's own and lagged conditional volatility. The persistence of each property return series is presented in Table 3. As shown, the three direct property return series exhibit higher persistence than the two indirect property return series. The persistence in the three direct property return series is 0.7267 (*OFF*), 0.8834 (*RET*) and 0.9117 (*IND*) and these imply volatility half-lives, defined as the time taken for the volatility to move halfway back towards its unconditional mean following a deviation from it, of 2.17 months for office returns, 5.59 months for retail property returns and 7.49 months for industrial property returns, where $HL = -\log(2)/\log(ARCH + GARCH)$. This means that for the direct property assets included in the analysis volatility shocks will tend to persist over what seem relatively long periods of time. By way of comparison, the half-lives of the indirect property returns are only 1.61 months for listed property trusts and just 0.22 months for property stocks.

Calculating the proportion of the initial shock remaining after different periods provides an alternative perspective. As shown in Table 3, 47 and 57 percent of the initial shock remains in direct retail and industrial property after six months, as against less than 15 percent in direct office property and less than 8 percent in listed property trusts. The proportion of volatility remaining six months after a shock for property stocks is zero. Even after eighteen months, 19 percent of the initial shock persists in industrial property and 11 percent in retail property. The suggestion is that listed and securitised property markets are better able to absorb the shocks to which they are exposed than direct property markets, while office property markets are better able to absorb shocks than retail or industrial property markets. Likely explanations of the former are the diversification benefits possible by incorporating direct property investment within property trusts and stocks, the ability of these entities to rebalance asset and liability portfolio levels, maturities and durations in response to shocks, their capacity to hold

derivatives and their combination of business and financial risk in a single entity. In the case of the latter, the booming residential property market and the substitutability of office and inner city, high-density developments, has improved the ability of the office property market to adjust in the face of shocks.

As a final requirement, the ability of the various models to accurately predict returns in each property market is examined. A simple indication of forecast ability is gained from the R^2 values in Table 2, but this is unable to identify the nature of any incorrect forecasts since it tracks the mean not the variance, and is only strictly applicable in least squares regression. More accurately, Table 3 provides an in-sample forecast evaluation for each estimated property equation. The Theil inequality coefficient always lies between zero and one, where zero indicates a perfect fit. For the purposes of forecasting property returns, the models used are clearly better at predicting direct office (0.3741), listed property trust (0.4151) and property stock (0.4265) returns than direct retail (0.8941) and industrial (0.8920) property returns.

The mean squared forecast error is also decomposed yielding the bias proportion (how far the mean of the forecast is from the mean of the actual series), the variance proportion (how far the variation of the forecast is from the variation of the actual series) and the covariance proportion (a measure of the remaining unsystematic forecasting errors). With direct office, listed property trust and property stocks most of the bias is appropriately concentrated in the covariance proportion (0.7186, 0.8901 and 0.7691, respectively), though the variance proportions for direct office (0.2472) and property stock (0.2284) indicate that these models have relatively greater difficulty in tracking the variance than listed property trusts (0.0862). With retail and industrial property returns most the forecast error is concentrated in the variance proportion (0.4891 and 0.5897, respectively) and this suggests that while the models are able to track the mean return in these markets (0.1353 and 0.1905, respectively) they are relatively poor at tracking the variance.

Conclusion

This study examines the role of macroeconomic risk factors in Australian property returns. Following earlier findings that property risk factor sensitivities and return premia are time varying, a generalised autoregressive conditional heteroskedasticity in mean (GARCH-M) technique is used to model the return generation process. As far as the authors are aware, this represents the first application of this methodology to property markets and adds significantly to our knowledge of the macroeconomic drivers that systematically affect property returns

within a multivariate framework. One of most important results is that there is much variation in the time-series properties among the types of property returns included in the sample, despite the fact that they share a common underlying asset base. While all of the returns exhibit the volatility clustering and predictability expected, the persistence of this volatility varies markedly with half-lives anywhere between less than a month to more than seven months. As expected indirect listed property markets are better able to absorb the shocks to which they are exposed than direct property markets, while office property markets are better able to absorb shocks than retail or industrial property markets.

There is also much variation in the influence macroeconomic factors have on property returns, with inflation being an influential factor in office, retail, industrial and listed property trust returns, industrial production being important in determining retail, industrial and listed property trust returns and employment being significant in office, retail and industrial returns. Interest rates are also a significant risk factor across all types of property portfolios, while the market return is a significant factor in retail, industrial, listed property trusts and property stocks. At least some of these results then concur with Ling and Naranjo's (1997, p. 296) conclusion that "the term structure of interest rates and unexpected inflation do not carry statistically significant risk premiums in the fixed-coefficient model but are significant when sensitivities and risk premia are allowed to vary over time" and Brooks and Tsolacos (1999, p. 150) who found "…some evidence that the interest rate term structure and unexpected inflation have a contemporaneous effect on property returns".

Nonetheless, the forecasting ability of these models also varies and this has implications for the usefulness of modelling property market performance using macroeconomic variables as systematic risk factors. Most notably, while macroeconomic factors are quite useful in forecasting returns in direct office and listed property trust and property stocks, they are less useful for forecasting returns in direct retail and industrial markets. At least part of the forecast bias in returns is provided by error in tracking mean returns in these property portfolios (some 16 percent on average), but the larger proportion is from difficulties in tracking the variance (about 54 percent on average). This contrasts sharply with direct office and listed property trust and property stock returns where errors in tracking the mean accounts for just 2 percent of error and only 19 percent of errors from tracking the variance. The presence of such large systematic forecast errors indicates that retail and industrial property models employing only macroeconomic factors are likely to be misspecified and points to the potential usefulness of other information. Microeconomic factors such as vacancy and lease rates are just one possibility.

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Table 1: Sample statistics of monthly property returns and changes in macroeconomic variables

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	JB	JB *p*-value	ρ	ρ *p*-value
OFF	0.0202	0.0227	0.0787	-0.0402	0.0286	-0.4189	3.2147	2.2438	0.3257	0.9310	0.0000
RET	0.0308	0.0280	0.0789	0.0127	0.0127	1.7583	6.6697	77.5014	0.0000	0.7560	0.0000
IND	0.0272	0.0321	0.0599	-0.0375	0.0199	-1.4901	5.0535	39.2960	0.0000	0.8590	0.0000
LPT	0.0291	0.0291	0.1176	-0.0870	0.0410	-0.3961	3.2055	2.0093	0.3662	0.1550	0.0968
STK	0.0101	0.0120	0.1971	-0.3358	0.0671	-1.5485	11.7024	255.9692	0.0000	-0.1520	0.1012
MKT	0.0298	0.0353	0.2470	-0.5219	0.0958	-2.4779	16.6139	629.6935	0.0000	-0.1880	0.0569
SBD	-0.0130	-0.0161	0.2933	-0.2002	0.1011	0.5481	3.3077	3.8887	0.1431	0.2500	0.0171
MBD	-0.0140	-0.0141	0.2045	-0.1990	0.0922	0.1488	2.5275	0.9358	0.6263	-0.0100	0.4668
LBD	-0.0133	-0.0199	0.1917	-0.1643	0.0760	0.3929	2.9319	1.8662	0.3933	0.1190	0.1597
EIN	0.0088	0.0096	0.0358	-0.0175	0.0111	0.0221	3.0699	0.0205	0.9898	0.8190	0.0000
UIN	-0.0002	0.0002	0.0513	-0.0462	0.0157	0.5181	5.0770	16.1632	0.0003	-0.0210	0.4305
CNS	0.0092	0.0185	0.8307	-0.7256	0.2651	0.1582	4.1114	4.0061	0.1349	-0.4190	0.0001
INP	0.0084	0.0073	0.0300	-0.0152	0.0101	-0.0479	2.4505	0.9333	0.6271	0.2920	0.0064
MNG	-0.0026	-0.0074	0.0728	-0.0624	0.0309	0.4804	2.6880	3.0612	0.2164	-0.1420	0.1171
MAN	-0.0005	-0.0020	0.0368	-0.0440	0.0172	0.0856	2.7692	0.2476	0.8836	0.1300	0.1382
ECO	-0.0036	-0.0062	0.0807	-0.0903	0.0404	0.0764	2.4095	1.1160	0.5723	-0.1820	0.0630
CST	0.0061	0.0096	0.0682	-0.0846	0.0289	-0.4969	4.0581	6.3212	0.0424	0.1080	0.1833
WRT	0.0019	-0.0013	0.0664	-0.0566	0.0232	0.1490	3.2999	0.5363	0.7648	-0.0930	0.2186
ARC	0.0083	0.0061	0.1201	-0.0683	0.0382	0.2231	2.9702	0.6002	0.7407	-0.1520	0.1012
TRN	0.0009	-0.0048	0.0899	-0.0638	0.0292	0.4600	3.1149	2.5793	0.2754	-0.1960	0.0495
FIN	0.0029	0.0005	0.0855	-0.0814	0.0322	0.2975	3.1086	1.0976	0.5777	-0.0050	0.4834
SER	0.0108	0.0131	0.0562	-0.0391	0.0205	-0.4523	3.1493	2.5219	0.2834	0.1010	0.1993
GOV	0.0040	0.0053	0.0368	-0.0342	0.0161	-0.1930	2.3471	1.7260	0.4219	-0.0770	0.2601

Notes: This table provides measures of central tendency, dispersion and shape for the monthly returns on the Australian Property Council's Office (OFF), Retail (RET) and Industrial (IND) Investment Performance Indexes, the Australian Stock Exchange's ASX/LPT 300 Listed Property Trust (LPT) Index, property sector index (STK) and All Ordinaries market (MKT) index and monthly changes in the 90-day Bank-Accepted Bill rate (SBD), 5-year (MBD) and 10-year (LBD) Commonwealth bond rate, expected (EIN) and unexpected (UIN) inflation rate, construction activity (CNS), industrial production (INP) and employment for the mining (MNG), manufacturing (MAN), utilities and telecommunications (ECO), construction (CST), wholesale/retail trade (WRT), accommodation and recreational services (ARC), transport (TRN), finance and insurance (FIN), property/business services (SER) and government administration (GOV) industries. The sample period is from March 1985 – December 2002. The critical values of skewness and kurtosis at the .05 level are 0.5658 and 0.5773, respectively, JB – Jarque-Bera, ρ – first-order autocorrelation coefficient, ρ *p*-value – one-tailed test of significance of first-order autocorrelation coefficient.

Table 2: Estimated coefficients for conditional mean return and conditional variance equations

	OFF			RET			IND			LPT			STK		
Variable	Coef.	Std. error	*p*-value	Coef.	Std. error	*p*-value	Coef.	Std. error	*p*-value	Coef.	Std. error	*p*-value	Coef.	Std. error	*p*-value
Mean equation															
GARCH	10.6503	3.9777	0.0074	0.0168	7.4825	0.9982	-0.7691	1.5720	0.6247	-19.1786	5.9489	0.0013	-10.2377	2.6292	0.0001
CON.	0.0031	0.0021	0.1328	0.0242	0.0008	0.0000	0.0314	0.0007	0.0000	0.0347	0.0037	0.0000	0.0212	0.0213	0.3202
MKT	0.0143	0.0103	0.1651	-0.0120	0.0058	0.0379	0.0107	0.0061	0.0796	0.2043	0.0258	0.0000	0.3074	0.0512	0.0000
SBD	0.0472	0.0133	0.0004	–	–	–	0.0152	0.0049	0.0021	–	–	–	–	–	–
MBD	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
LBD	–	–	–	0.0152	0.0054	0.0047	–	–	–	-0.2052	0.0249	0.0000	-0.1967	0.0696	0.0047
EIN	0.7709	0.1275	0.0000	0.1294	0.0491	0.0084	-0.1285	0.0554	0.0203	-0.2775	0.1550	0.0734	0.0506	0.5611	0.9281
UIN	0.3407	0.0631	0.0000	0.0151	0.0408	0.7119	-0.0960	0.0259	0.0002	-0.2049	0.0913	0.0248	-0.0035	0.3018	0.9907
CNS	0.0069	0.0032	0.0306	-0.0050	0.0027	0.0598	-0.0028	0.0021	0.1883	0.0209	0.0089	0.0182	0.0205	0.0232	0.3780
INP	0.0354	0.1341	0.7916	0.1945	0.0562	0.0005	0.1123	0.0420	0.0075	0.7505	0.2600	0.0039	-0.1028	0.6874	0.8811
MNG	0.0844	0.0316	0.0076	0.0170	0.0170	0.3176	-0.0504	0.0172	0.0033	0.0406	0.0472	0.3897	-0.0091	0.1521	0.9521
MAN	0.1123	0.0528	0.0334	0.0777	0.0301	0.0098	-0.0174	0.0221	0.4309	0.0393	0.0850	0.6442	-0.2842	0.2844	0.3177
ECO	0.0387	0.0212	0.0675	-0.0021	0.0159	0.8952	-0.0267	0.0095	0.0051	-0.1962	0.0455	0.0000	-0.2514	0.1416	0.0758
CST	0.1220	0.0362	0.0008	0.0329	0.0136	0.0154	-0.0355	0.0253	0.1600	0.1487	0.0810	0.0665	0.4119	0.2118	0.0518
WRT	0.0484	0.0410	0.2378	-0.0155	0.0292	0.5952	0.0357	0.0181	0.0494	-0.1092	0.0931	0.2410	-0.5434	0.2768	0.0497
ARC	-0.0570	0.0250	0.0224	-0.0164	0.0142	0.2472	-0.0053	0.0068	0.4341	0.0165	0.0482	0.7323	-0.1505	0.1597	0.3460
TRN	0.0657	0.0340	0.0536	0.0246	0.0206	0.2332	-0.0216	0.0160	0.1778	-0.0303	0.0660	0.6462	0.1145	0.1497	0.4447
FIN	0.1014	0.0338	0.0027	-0.0127	0.0184	0.4908	-0.0216	0.0178	0.2260	0.1946	0.0617	0.0016	0.1751	0.1721	0.3090
SER	0.2239	0.0568	0.0001	-0.0014	0.0247	0.9544	0.0290	0.0182	0.1109	-0.4350	0.0687	0.0000	-0.1571	0.2380	0.5092
GOV	0.0492	0.0642	0.4431	0.0530	0.0425	0.2126	0.0206	0.0246	0.4035	0.1607	0.0803	0.0454	0.4543	0.3993	0.2553
Variance equation															
CON.	0.0001	0.0003	0.7862	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004	0.0002	0.0207	0.0021	0.0043	0.6295
ARCH(1)	0.8852	0.2095	0.0000	0.5796	0.1941	0.0028	1.1426	0.2249	0.0000	0.8388	0.2426	0.0005	-0.1001	0.0327	0.0022
ARCH(2)	-0.2666	2.2571	0.9060	-0.0695	0.1946	0.7211	-0.4235	0.1900	0.0258	–	–	–	–	–	–
GARCH(1)	-0.0168	2.4951	0.9946	0.5227	0.2149	0.0150	0.2856	0.1763	0.1053	-0.1891	0.1396	0.1754	0.1448	1.9311	0.9402
GARCH(2)	0.1249	0.6924	0.8568	-0.1494	0.0872	0.0867	-0.0930	0.0485	0.0554	–	–	–	–	–	–
R-squared	0.4655	–	–	0.1456	–	–	0.0508	–	–	0.4081	–	–	0.4787	–	–
F-statistic	1.9396	–	–	0.3795	–	–	0.3811	–	–	1.7581	–	–	2.3416	–	–
p-value	0.0274	–	–	0.9922	–	–	0.9897	–	–	0.0537	–	–	0.0075	–	–

Notes: This table provides the estimated coefficients, standard errors and *p*-values from the conditional mean return and variance equations for the five measures of property returns, namely: the Australian Property Council's Office (OFF), Retail (RET) and Industrial (IND) Investment Performance Indexes and the Australian Stock Exchange's ASX/LPT 300 Listed Property Trust (LPT) Index and property sector index (STK). The macroeconomic variables specified in the mean equation are the ASX All Ordinaries market index (MKT), 90-day Bank-Accepted Bill rate (SBD), 5-year (MBD) and 10-year (LBD) Commonwealth bond rate, expected (EIN) and unexpected (UIN) inflation rate, construction activity (CNS), industrial production (INP) and employment for the mining (MNG), manufacturing (MAN), utilities and telecommunications (ECO), construction (CST), wholesale/retail trade (WRT), accommodation and recreational services (ARC), transport (TRN), finance and insurance (FIN), property/business services (SER) and government administration (GOV) industries. CON. – constant.

Table 3: Volatility persistence analysis and specification, joint significance and forecast performance tests

Type	Statistic and significance	OFF	RET	IND	LPT	STK
Volatility effects	Persistence	0.7267	0.8834	0.9117	0.6497	0.0447
	Half life	2.1712	5.5909	7.4980	1.6073	0.2230
	6-month shock	14.7276	47.5274	57.4264	7.5210	0.0000
	12-month shock	2.1690	22.5886	32.9779	0.5657	0.0000
	18-month shock	0.3194	10.7358	18.9380	0.0425	0.0000
	24-month shock	0.0470	5.1024	10.8754	0.0032	0.0000
Autocorrelation tests	ARCH LM *F*-statistic	0.7190	0.7779	0.5651	0.4663	0.7716
	ARCH LM *p*-value	0.7779	0.5260	0.9079	0.9612	0.7247
Joint significance tests	Inflation *W*-statistic	43.7237	5.2012	17.6983	5.0251	0.0045
	Inflation *p*-value	0.0000	0.0226	0.0000	0.0250	0.9464
	Production *W*-statistic	0.0982	11.0273	6.6326	8.7225	0.0140
	Production *p*-value	0.7540	0.0009	0.0100	0.0031	0.9059
	Employment *W*-statistic	33.1853	7.7859	2.7335	0.9680	0.1961
	Employment *p*-value	0.0000	0.0053	0.0983	0.3252	0.6579
Forecast evaluations	Theil Inequality Coef.	0.3741	0.8941	0.8920	0.4151	0.4265
	Bias proportion	0.0342	0.1353	0.1905	0.0236	0.0025
	Variance proportion	0.2472	0.4891	0.5897	0.0862	0.2284
	Covariance proportion	0.7186	0.3757	0.2198	0.8901	0.7691

Notes: This table presents a volatility persistence analysis and specification, joint significance and forecast performance tests for the Australian Property Council's Office (OFF), Retail (RET) and Industrial (IND) Investment Performance Indexes and the Australian Stock Exchange's ASX/LPT 300 Listed Property Trust (LPT) Index and property sector index (STK) return models in Table 2. Persistence is the sum of the estimated ARCH and GARCH coefficients. ARCH LM is the Lagrange multiplier test for higher-order autoregressive conditional heteroskedasticity. The joint significance tests are Wald tests that all coefficients are jointly zero for inflation (EIN and UIN), production (including industrial and construction activity) (CNS and INP) and employment (MNG, MAN, ECO, CST, WRT, ARC, TRN, FIN, SER and GOV). CON – constant.