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Predicting Securitized Real Estate Returns: Financial and Real Estate Factors vs. Economic Variables

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Predicting Securitized Real Estate Returns: Financial and Real Estate Factors vs. Economic Variables

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Abstract

Securitized real estate returns have traditionally been forecasted using economic variables. However, no consensus exists regarding the variables to use. Financial and real estate factors have recently emerged as an alternative set of variables useful in forecasting securitized real estate returns. This paper examines whether the predictive ability of the two sets of variables differs. We use fractional cointegration analysis to identify whether long-run nonlinear relations exist between securitized real estate and each of the two sets of forecasting variables. That is, we examine whether such relationships are characterized by long memory, short memory, mean reversion (no long-run effects) or no mean reversion (no long-run equilibrium). Empirical analyses are conducted using data for the U.S., the U.K., and Australia. The results show that financial and real estate factors generally outperform economic variables in forecasting securitized real estate returns. Long memory (long-range dependence) is generally found between securitized real estate returns and stocks, bonds, and direct real estate returns, while only short memory is found between securitized real estate returns and the economic variables. Such results imply that to forecast securitized real estate returns, it may not be necessary to identify the economic variables that are related to changing economic trends and business conditions.

Keywords: Fractional Cointegration, Fractionally Integrated Error Correction Model (FIECM), Forecasting, Multifactor Models, Securitized Real Estate, REITs

JEL Classifications: G17, G11, C53

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1 Introduction

Listed real estate security markets have experienced substantial growth in the last decade both in the U.S. and internationally. An increasing number of portfolio managers are considering such vehicles as a substitute or in addition to direct real estate holdings. Knowing how best to forecast the returns of these securities is thus of importance. Two sets of factors have been used in the literature when examining the driving factors of securitized real estate returns. One set has examined the linkages with economic variables (Chan, Hendershott and Sanders 1990, McCue and Kling 1994, Ling and Naranjo 1997), while the other has focused on the linkages with financial assets and real estate (Clayton and MacKinnon 2001, 2003, Hoesli and Serrano 2007). The usefulness of employing economic variables to forecast securitized real estate returns has been established by Liu and Mei (1992), Bharati and Gupta (1992), Mei and Liu (1994), and Brooks and Tsolacos (2001, 2003), while Serrano and Hoesli (2007) have used financial and real estate assets’ returns to forecast EREIT returns. A question that arises is whether securitized real estate returns are more predictable with economic variables or with financial and real estate factors.

This question is of outmost importance as identifying the economic variables that exert an influence on securitized real estate returns has proven to be a difficult task. This is evidenced by the conflicting results contained in the extant literature. However, if securitized real estate is viewed as a hybrid of financial and direct real estate assets, then these factors can be used as proxies for the set of economic variables related to changing economic trends and business conditions. This paper provides a contribution to this debate by determining if financial and real estate factors represent a useful alternative to economic variables for the purpose of forecasting securitized real estate returns and constructing profitable trading strategies.
Another contribution of this paper is that it explains why the prediction results differ. This is done by examining whether long-run nonlinear relationships exist between real estate securities and the economic variables, and between real estate securities and the financial and real estate factors. For this purpose, we estimate the degree of cointegration between securitized real estate and the two sets of forecasting variables. The degree of cointegration determines the existence of long memory (long-range dependence), short memory (short-range dependence), no long-run effects (mean reversion) or no long-run equilibrium (no mean reversion; the process drifts away from its equilibrium permanently). Therefore, the paper’s contribution is also in identifying the dynamics that govern the relationships between securitized real estate and the two sets of forecasting variables, and in determining whether the outperformance of one set of forecasting variables over the other is due to the nature of their nonlinear linkages with securitized real estate.

Two forecasting specifications are tested for the economic variables, i.e., the model employed by Chan, Hendershott and Sanders (1990) and that employed by Liu and Mei (1992). The former model includes bond and inflation related variables, while the latter comprises bond and performance related variables. A third forecasting specification uses stocks, bonds, and direct real estate as the predictive variables. Data for the U.S., the U.K., and Australia are used. These countries are three of the six largest securitized real estate markets and account for 41% of the global securitized real estate market capitalization. Due to data availability, the analysis for the U.S. is for 1980-2008Q2, whereas the time period is 1987-2008Q2 for the U.K. and Australia. The major difference between these markets is that in the U.S. and Australia, real estate securities have tax-transparency (REIT status) during the whole period studied, while in the U.K., REIT status was only established at the end of the time period.
considered (in 2007). Another important difference concerns the leverage employed by these companies in the different countries, with real estate securities in the U.S. being far more leveraged than real estate securities in the U.K. and in Australia.\(^1\)

Our findings suggest that financial and real estate factors outperform economic variables in forecasting securitized real estate returns in the U.S. and Australia. This can be explained by the presence of long memory (long-range dependence) between securitized real estate and stocks, bonds, and real estate. Such long-run relationship between securitized real estate and the financial and real estate factors does not exist in the U.K., and hence these variables do not perform well in the U.K for prediction purposes. The only other specification to exhibit long memory is that of Chan, Hendershott and Sanders (1990) in Australia. However, in the U.S. and the U.K., no long-run effects are found between securitized real estate and these economic variables. Finally, the economic variables of Liu and Mei (1992) are found to exhibit short-term memory with securitized real estate in the three countries. The results obtained when the forecasts are employed in an active investment strategy are consistent with these findings.

The paper is organized as follows. The next section offers a review of the relevant literature. The third section provides a description of the data, while the fourth section presents the methodology. The section that follows contains the results, and the last section provides some concluding remarks.

\(^1\)As of the end of 2007, the average debt/equity ratio of the five largest real estate securities in each country was 2.67 in the U.S., 0.83 in the U.K., and 0.76 in Australia.
2 Literature Review

2.1 Factors Explaining Asset Returns

Economic variables have been commonly used in the financial economics literature to examine the behavior and predictability of asset returns. Chen, Roll and Ross (1986) test whether innovations in macroeconomic variables affect stock market returns. The sources of risk that are significantly priced by the market are the spread between long- and short-term interest rates, expected and unexpected inflation, industrial production, and the spread between high- and low-grade bonds. Keim and Stambaugh (1986) try to identify \textit{ex ante} observable variables that reliably predict \textit{ex post} risk premiums (i.e., returns in excess of the short-term interest rate) on a wide range of assets. They find that the spread between yields on low-grade corporate bonds and one-month bills, the negative logarithm of the ratio of the real stock index to its previous historical average, and the negative logarithm of share prices averaged across the quintile of firms with the smallest market values, predict \textit{ex post} risk premiums of common stocks of various sizes, long-term bonds of various default risks, and government bonds of various maturities.

Campbell (1987) presents evidence that the state of the term structure of interest rates predicts excess returns of stocks, bills, and bonds. As indicators of the state of the term structure, he uses the one-month bill rate, the spread between the two- and one-month rate, the spread between the six- and one-month rate, and the one lag excess return on two- over one-month bills. Fama and French (1989) present empirical evidence that the excess returns of stocks and bonds may be forecasted with the default spread (the difference between the yield on a market portfolio of corporate bonds and the yield on AAA bonds), the term spread (the difference between the AAA yield and the one-month bill rate), and the dividend yield. More recently, Laopodis (2006) examines the
dynamic interactions among the stock market, economic activity, inflation, and monetary policy, and finds that the relationships vary across time.

In the U.K., Diacogiannis (1986), Poon and Taylor (1991), and Cheng (1995) show that the macroeconomic variables of Chen, Roll and Ross (1986) are not useful to predict stock returns. However, various economic variables are analyzed in the U.K. by Beenstock and Chan (1988), Clare and Thomas (1994), Priestley (1996), and Antoniou, Garrett and Priestley (1998), and some of the variables appear to be priced in the stock market, although the results lack consistency across the studies. In Australia, Groenewold and Fraser (1997) and Yao, Gao and Alles (2005) find that the factors priced in the stock market overlap considerably with those found in the U.S. At an international level, more recent studies examining the effects of economic variables on global stock market returns include Cheung and Lai (1998), Cheung and Ng (1998), Aylward and Glen (2000), Fifield, Power and Sinclair (2002), and Wongbangpo and Sharma (2002).

In the securitized real estate literature, Chan, Hendershott and Sanders (1990) use the macroeconomic variables proposed by Chen, Roll and Ross (1986) and find that the spread between high- and low-grade bonds, the slope of the term structure of interest rates, and unexpected inflation have explanatory power, while changes in expected inflation and industrial production do not. In addition to these macroeconomic variables, Ling and Naranjo (1997) also use the real T-bill rate and the growth rate of per capita consumption. They conclude that the growth rate in real per capita consumption, the real T-bill rate, the term structure of interest rates and unexpected inflation have systematic influences on commercial real estate returns. However, Chen et al. (1998) report that the macroeconomic variables are not significant when size and book-to-market variables are included in the model. Payne (2003) and Ew-
ing and Payne (2005) study the effects that shocks to macroeconomic variables have on REITs. They find that shocks to monetary policy, economic growth, and inflation lead to lower than expected returns, while shocks to the default risk premium are associated with higher future returns.

McCue and Kling (1994) use the pre-specified macroeconomic variables of the physical capital investment model of Lawrence and Siow (1985) and find that nominal interest rates have the most significant influence on REIT returns. In the U.K., Brooks and Tsolacos (1999) examine securitized real estate returns purged of general stock market influences by employing a VAR methodology to determine the impact of macroeconomic variables used in studies with U.S. data. Their results indicate that unexpected inflation and the term structure of interest rates have explanatory power. However, lagged values of the securitized real estate series have the most significant influence, while the rate of unemployment, nominal interest rates, and the dividend yield have no impact. A recent study of Liow and Webb (forthcoming) investigates the economic variables that affect four of the largest securitized real estate markets (the U.S., Hong Kong, the U.K., and Singapore) and find that the number, as well as the factors that have an impact, vary across countries.

Another possibility to explain asset returns is to determine the relevant risk factors endogenously by relying on factor analysis techniques that simultaneously estimate the factors and factor loadings of security returns. Such statistical factors are constructed by Roll and Ross (1980) in their Factor Loading Model (FLM). For the securitized real estate market, it has been implemented by Titman and Warga (1986). We do not consider statistical factors for our forecast comparisons as Chen, Hsieh and Jordan (1997) established that the FLM is usually outperformed by a model using the pre-specified macroeconomic variables of Chen, Roll and Ross (1986).
It is also possible to consider securitized real estate as a hybrid asset of stocks, bonds and real estate (Clayton and MacKinnon 2001, 2003). The reason for this is that real estate securities are stocks with generally stable cash flows derived from income producing real estate. Thus, stock-like characteristics appear in real estate securities as they are publicly traded, bond-like features emerge from the generally long-term fixed leases that generate a fixed income, and real estate-like attributes arise from the underlying real estate assets. Abundant literature exists linking securitized real estate to financial assets (Peterson and Hsieh 1997, Karolyi and Sanders 1998, Ling and Naranjo 1999), as well as to real estate (Giliberto 1990, Gyourko and Keim 1992, Mei and Lee 1994). Overall, the general conclusions at an international level point to securitized real estate returns being positively related to stock and real estate returns, but negatively related to bond returns (Hoesli and Serrano 2007).

The variation of these linkages through time has also been the subject of much research. Clayton and MacKinnon (2003) find that the economic factors driving REIT returns during the 1970s and 1980s were the same as those driving large cap returns, but in the 1990s REIT returns became more strongly related to both small caps and real estate related factors. Anderson et al. (2005) separate small cap stocks into value and growth categories and find that REITs behave more like small cap value stocks than like small cap growth stocks or large cap stocks.

Some research has also examined whether real estate securities are cointegrated with other assets or economic variables. Wilson and Okunev (1999) find no evidence to suggest long co-memories between stock and securitized real estate markets in the U.S. and the U.K., but some evidence of this in Australia. Glascock, Lu and So (2000) report that U.S. REITs were cointegrated with bonds and inflation until 1992 and to stocks, particularly small caps, thereafter.
A generalized version of cointegration, named fractional cointegration, has been used to analyze the existence of nonlinear long-run relationships. In the financial economics literature, it was initially employed by Cheung and Lai (1993) in an examination of purchasing power parity, and by Baillie and Bollerslev (1994) in an exchange rate context. In the securitized real estate literature, Liow and Yang (2005) examine several economies of the Asia-Pacific region and offer reasonable support for fractional cointegration (i.e., the presence of a long memory process) between securitized real estate prices, stock prices, and key macroeconomic factors (GDP, inflation, money supply, short-term interest rate, and exchange rate).

2.2 Securitized Real Estate Returns Forecasting

The literature on the predictability of securitized real estate returns has generally favored multivariate models over univariate models. The accuracy of the forecasts of several multivariate techniques has been examined, but no single technique has turned out to be universally superior. As for the forecasting variables used, economic variables have been employed in all the studies except for Serrano and Hoesli (2007). They use the hybrid nature of EREITs to compare the predictive potential of four different model specifications with time varying coefficient (TVC) regressions, VAR systems, and neural networks models. Their results show that the best predictions are obtained with the neural networks model, particularly when stock, bond, real estate, size, and book-to-market factors are used.

All other research has relied on economic variables for prediction purposes. Liu and Mei (1992) find that cap rates are an important determinant of EREITs expected excess returns as they contain useful information about the general risk condition in the economy. Mei and Liu (1994) use the multi-factor latent-
variable model of Liu and Mei (1992) to predict the time variation of expected excess returns on various asset classes. They find that higher trading profits can generally be achieved for real estate stocks than for small cap stocks, large cap stocks, and bonds. Bharati and Gupta (1992) extend the work of Liu and Mei (1992) by examining a richer set of predictive variables (14 in total) and testing whether investors can profit from such predictability. They find that an active trading strategy using the returns predicted by their model outperforms a passive investment.

Brooks and Tsolacos (2001) use several time series techniques to examine the predictability of securitized real estate returns in the U.K. The forecasting variables retained are: lagged securitized real estate returns, the term spread, and the gilt-equity yield ratio. They show that a VAR model which incorporates financial spreads exhibits a better short-term out-of-sample forecasting performance than univariate time series models, but that for longer time horizons, the best forecasts are obtained using the long-term mean of the series. However, the forecasts do not generate excess returns over a buy-and-hold investment when transaction costs are taken into account. Brooks and Tsolacos (2003) analyze the performance of various forecasting models and commonly used financial indicators for predicting securitized real estate returns in five European countries (the U.K., Belgium, the Netherlands, France, and Italy). They show that in a VAR framework, the gilt-equity yield ratio is generally a better predictor than the term structure or the dividend yield. Additionally, they find that neural networks models generally lead to the most accurate predictions.

Overall, the existing literature on the predictability of securitized real estate returns has focused on testing the forecasting ability of various economic variables. The conclusions are mixed, so choosing the economic variables to include in a forecasting model is problematic. A recent alternative has emerged. It
consists of using financial and real estate factors as forecasting variables that proxy for the set of economic variables related to changing economic trends and business conditions. This paper contributes to the literature by identifying and depicting the long-run nonlinear relationships between securitized real estate and economic, and financial and real estate variables, respectively, and consequently, by determining which set of variables provides better securitized real estate return forecasts.

3 Data

The data used in this study were mainly sourced from Thomson Datastream and cover the period 1980-2008Q2 for the U.S., and 1987-2008Q2 for Australia and the U.K. According to the GPR General Global index as of 2008Q2, these three countries are, respectively, the first, fifth, and sixth largest securitized real estate markets in the world in terms of market capitalization. Together, they account for 41% of global securitized real estate markets (the U.S. 25.7%, Australia 8.3%, and the U.K. 6.7%). The starting dates of the samples were dictated by the availability of the corporate bonds data in the U.S., the direct real estate data in the U.K., and the government bonds data in Australia, while the frequency used was dictated by several of the variables whose data are released on a quarterly basis. For securitized real estate, the FTSE/NAREIT All REITs total return index is used for the U.S. and the GPR General Property Share total return index for the U.K. and Australia. Returns are forecasted by means of three model specifications. Two specifications use economic variables and a third one uses financial and real estate factors. While several economic variables have been tested in the literature, no consensus exists regarding the best specification. Therefore, we test two forecasting specifications, i.e., the model employed by Chan, Hendershott and Sanders (1990) and that employed
A summary of the forecasting variables used in this paper is provided in Table 1. Panel A contains the raw economic series. The two sets of economic variables are shown in Panel B. First, the set used by Chan, Hendershott and Sanders (1990), then the one used by Liu and Mei (1992). The former set includes bond and inflation related variables, while the latter comprises bond and performance related variables. Finally, the financial and real estate factors appear in Panel C. Such factors include Datastream’s total return stock index, $S_t$, Datastream’s 10-year total return government bond index, $B_t$, and for the real estate factor, $RE_t$, the NCREIF Property Index (NPI) in the U.S., the IPD index in the U.K., and the Mercer Unlisted Property Fund Index (MUPFI) in Australia. As the Property Council of Australia (PCA) index is only available at a quarterly frequency since 1995Q2 (at a semi-annual frequency since 1984H2), we use the MUPFI.\footnote{At a semi-annual frequency, the correlation between the PCA index and the MUPFI is 0.96 for the period 1985H1 to 2008H1.} One common problem with appraisal-based real estate returns is the smoothing issue (Geltner 1993, Fisher, Geltner and Webb 1994). Therefore, we desmooth the real estate indices using Geltner’s (1993) approach. Summary statistics of all the variables used are available in Table 2.

4 Methodology

4.1 Fractional Cointegration

First, we characterize the long-run nonlinear dynamics that could link securitized real estate to the two sets of economic variables tested, as well as to the financial and real estate factors. For that purpose, fractional cointegration tests are performed. That is, we estimate the degree of cointegration, $I(d)$, between the dependent variable and the three specifications used. The presence,
lack, and ultimately, the degree of fractional cointegration, allow to identify the existing relationship between securitized real estate and the three sets of explanatory variables. Depicting these linkages should prove useful in explaining the differences in predictability across the different specifications.

Empirical studies in macroeconomics and finance usually involve the use of non-stationary series such as price levels, exchange rates, income, consumption or money demand. Rendering such series stationary by differencing, taking logs, or making any other transformation has been a common practice in order to analyze the resulting series with Box and Jenkins methods or with VARs. However, an interesting body of literature concerns the analysis of non-stationary time series. As such, the level series of securitized real estate and of the variables are used in the three specifications to determine if they are fractionally cointegrated, i.e., to establish whether nonlinear long-run equilibrium relationships exist among the variables.

A time series is said to be integrated of order $d$, denoted $I(d)$, if it can achieve stationarity after differencing it $d$ times; $d$ being an integer. Engle and Granger (1987) demonstrate that a linear combination of two or more non-stationary series may be stationary. Such series are said to be cointegrated. The stationary linear combination is called the cointegrating equation and may be interpreted as a long-run equilibrium relationship among the variables. The standard approach used to test for cointegration is Johansen’s (1988, 1991) linear Full Information Maximum Likelihood (FIML) technique.$^3$

Fractional cointegration examines a broader characterization of a long-run economic relation than cointegration. It refers to the case in which two process with the same degree of integration have an equilibrium error that is $I(d)$, with $d$ defined as any real number less than one. This relaxes the $I(0)$ error term.

$^3$For a review of the theory and empirical applications of this methodology, see Hargreaves (1994).
requirement in the traditional cointegration specification. Thus, fractional coi-
tegration associates the existence of a long-run relationship with mean reversion
in the error term, rather than requiring both mean reversion and stationarity.

The presence of a long-run equilibrium relationship when $d$ is a non-integer
real number less than one entails that nonlinearities are at play and that the
equilibrium error may still be mean-reverting. The mean reversion behavior
depends primarily on the value of the fractional differencing parameter, $d$. The
interpretation of the degree of integration is as follows (Hosking 1981). A process
displays long memory (long-range dependence) when $0 < d < 0.5$, short memory
(short-range dependence) when $-0.5 < d < 0$, no long-run effect (mean rever-
sion) when $0.5 < d < 1$, and no mean reversion (the process drifts away from
its equilibrium permanently) when $d > 1$. Long- and short-range dependent
processes are characterized by their autocovariance functions. In short-range
dependent processes, the coupling between values at different points in time
decreases rapidly as the time difference increases. That is not the case in long-ange dependent processes, where the coupling lasts much longer. Therefore, the
autocovariance function exhibits an exponential decay near zero in the presence
of short memory and a hyperbolic decay when there is long memory. Stated
differently, a long or short memory process may be defined according to whether
its correlations have an infinite or finite sum.

To estimate the fractional cointegration parameter, $d$, the following three-
step procedure is followed. First, we estimate the order of integration for each
series as it must be the same for all the series in order to perform cointegration
analysis. For that purpose, Augmented Dickey-Fuller (ADF) tests are performed
to determine the presence of a unit root (non-stationarity) in all the series. Then,
a cointegration regression is performed for each specification tested:
Economic Variables of Chan, Hendershott and Sanders (1990)

\[ Y_t = \alpha_0 + \alpha_1 \Delta TS_t + \alpha_2 \Delta RP_t + \alpha_3 EI_t + \alpha_4 \Delta EI_t + \alpha_5 UI_t + z_{at} \]  

(1)

Economic Variables of Liu and Mei (1992)

\[ Y_t = \theta_0 + \theta_1 TB_t + \theta_2 YS_t + \theta_3 DY_t + \theta_4 CR_t + z_{bt} \]  

(2)

Financial and Real Estate Factors

\[ Y_t = \psi_0 + \psi_1 S_t + \psi_2 B_t + \psi_3 RE_t + z_{ct} \]  

(3)

where \( Y_t \) is the level of the securitized real estate series, the explanatory variables are those defined in Table 1, and \( z_{it} \) are the respective residual series.

The residual series, \( z_{it} \), are examined for the existence of fractional cointegration by estimating the fractional cointegration parameter, \( d \), with Geweke and Porter-Hudak’s (1983) fractional differencing test for long memory. Basically, this technique examines the behavior of the spectral density near zero. This means that the log periodogram is regressed on log frequencies around zero to calculate the slope coefficient. This coefficient provides a consistent estimator of the fractional differencing parameter. The spectral regression is as follows:

\[
\ln(I_u(\omega_j)) = \alpha + \beta \ln(4 \sin^2(\omega_j/2)) + \varepsilon_t \quad \text{for} \ j = 1,2,\ldots,n 
\]

(4)

where \( I_u(\omega_j) = \frac{1}{2\pi T} \sum_{t=1}^{T} e^{i\omega(z_t - \tau)} \) is the periodogram of \( z_t \) at frequency \( \omega_j \), \( \beta = 1 - d \), \( \varepsilon_t = \ln(I_u(\omega_j)/f_u(\omega_j)) \) is assumed to be i.i.d. with theoretical asymptotical mean and variance equal to 0 and \( \pi^2/6 \), respectively, \( T \) is the number of observations, and \( n = f(T) = T^\mu \) for \( 0 < \mu < 1 \) is the number of low-frequency ordinates used in the regression. For the sample size function
$n = T^n$, we report results for $\mu = 0.55, 0.575, \text{ and } 0.60$, as suggested by Geweke and Porter-Hudak (1983).

Since the mean reversion behavior of the equilibrium error depends more on the range as opposed to the exact value of the fractional differencing parameter, $d$, we provide the confidence intervals at a 95% level. The confidence intervals give a clearer idea of the behavior of the residual series of the cointegration regression and, therefore, of the linkages between the dependent variable and the three forecasting specifications. The critical values for the GPH test are nonstandard, so those derived from the standard distribution cannot be used. In fact, the residual series of the cointegration regression tends to be biased toward being stationary. Therefore, we employ the critical values provided by Sephton (2002) who performs Monte Carlo estimates of the critical values to use in fractional cointegration tests.

### 4.2 Fractionally Integrated Error Correction Model

The presence of a cointegrating relation forms the basis of the Error Correction Model (ECM). Even though cointegrated variables display a long-run equilibrium relationship, short-run dynamics cause deviations from this equilibrium. This short-run behavior may be tied to the long-run equilibrium by the error correction term. The advantage of modeling the cointegration relationship by a fractional process lies in its incorporation of the effects of long memory. While the ECM only takes into account the first-order lag of the cointegration residual series, the Fractionally Integrated Error Correction Model (FIECM) incorporates a long history of past cointegration residuals. The FIECM model may be

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4Note that a large value of $n$ may contaminate the estimation of $d$ due to the high/medium frequency components, but a small value of $n$ will lead to imprecise estimates due to the limited degrees of freedom.
defined as follows:

$$\Delta \ln Y_t = \phi_0 + \sum_{i=1}^{I} \phi_i \Delta \ln X_{t-i} + \delta[(1 - L)^d - (1 - L)]z_{t-i} + \varepsilon_t$$

(5)

where $\Delta \ln Y_t$ is the logarithmic difference of the level securitized real estate series, $\Delta \ln X_{t-i}$ is the logarithmic difference of the lagged set of explanatory variables in their levels\(^5\), and $\delta[(1 - L)^d - (1 - L)]z_{t-i}$ is the fractionally integrated error correction term in which $L$ is the lag operator, $d$ is the order of integration, and $z_t$ is the vector of residuals from the cointegration regression. The polynomial within the square brackets can be expanded so that the coefficient of $z_{t-i}$ is equivalent to $\delta \Gamma(i - d)/\{\Gamma(-d)\Gamma(i + 1)\}$, where $\Gamma(\cdot)$ is the gamma function defined as $\Gamma(x) = \int_0^\infty t^{x-1} e^{-t} dt$ for $x > 0$ and as $\Gamma(x) = \frac{\Gamma(x+1)}{x}$ for $x < 0$.

The active trading strategies are constructed as follows. One-quarter-ahead forecasts of securitized real estate total returns are performed with a FIECM for each of our three specifications. Such forecasts are constructed dynamically using a rolling window with 50 observations for in-sample parameter estimation. Out-of-sample forecasts are obtained by re-estimating the parameters at each step and shifting the window sample by one observation until the whole sample is exhausted. The forecasts are performed over 34 out-of-sample quarters for the three countries in order to use a common period (i.e., 2000Q1-2008Q2 for all countries). Such forecasts are employed in an active trading strategy that is benchmarked against a buy-and-hold investment. Under the assumption that an investor takes a long position either on real estate securities or on the risk free asset, the following trading rules are applied. If securitized real estate return forecasts are higher than the risk free asset’s return, the investor will go long

\(^5\)The optimal number of lags used for each set of explanatory variables is determined according to the Schwarz Bayesian information criterion (SBC). The longest specification tested included four lags and the SBC criterion led to an optimal number of lags of one for the three sets of variables.
on real estate securities; otherwise the investor will go long the risk free asset. Potential gains are put into perspective with the transaction costs associated with such strategies.

5 Empirical Results

5.1 Fractional Cointegration Results

Augmented Dickey-Fuller (ADF) tests are performed on the level of all the series used to determine the presence of a unit root. All the series are non-stationary (i.e., they have a unit root) except for unexpected inflation, $UI_t$, in the three countries. Since cointegration analysis requires the series to be non-stationary, this variable is omitted from the cointegration regression of the Chan, Hendershott and Sanders (1990) specification. Table 3 shows the estimated fractional cointegration coefficients, $d$, for each of the forecasting models in each country. Three estimations are performed with different values of $\mu$ (0.55, 0.575, and 0.60). The results for each value of $\mu$ are similar, giving a clear idea of the range of $d$ for each model in each country.

More specifically, we find that securitized real estate exhibits long-range dependence (long memory) with the financial and real estate factors in the U.S. and Australia ($0 < d < 0.5$), but no long-run effects (mean reversion) in the U.K. ($0.5 < d < 1$). The economic variables of Liu and Mei (1992) generally outperform the economic variables of Chan, Hendershott and Sanders (1990) as securitized real estate displays short-range dependence (short memory) with the specification of Liu and Mei (1992) in the three countries ($-0.5 < d < 0$), therefore indicating some predictability. Finally, we find that the economic variables of Chan, Hendershott and Sanders (1990) have no long-run effects on securitized real estate in the U.S. and the U.K. as the estimated degree of cointegration
(0.5 < d < 1) indicates that this specification is mean reverting. However, these economic variables have good predictability in Australia where evidence of long-range dependence (long memory) is found. Overall, these findings suggest that the model using financial and real estate factors should generally obtain the highest predictability. There might also be some predictability with the economic variables of Liu and Mei (1992), but with those of Chan, Hendershott and Sanders (1990), there is generally no predictability.

It is important to note that a process is likely to present varying dynamics through time. Whereas the characterization of the linkages in one of the above mentioned ranges is the most likely behavior, it does not exclude the presence of other types of behavior from time to time. Indeed, as the long-run equilibrium linkages are defined in terms of ranges rather than single values, quite large confidence intervals are to be expected. Consequently, other than the main behavior described above, these intervals show that the financial and real estate factors could at times exhibit short memory, the economic variables of Liu and Mei (1992) could also display some long memory, and the economic variables of Chan, Hendershott and Sanders (1990) could drift away from equilibrium permanently in the U.S. and the U.K.

5.2 Forecasting Results

The trading results for each of the forecasting models and countries are shown in Table 4. For the 34 out-of-sample forecasts, the best performing models are the financial and real estate factors model in the U.S. and Australia, and the Liu and Mei (1992) model in the U.K. In the U.S., only the active strategy using the financial and real estate factors (15.57% p.a.) outperforms the buy-and-hold investment (14.32% p.a.). In the U.K., the only strategy to outperform the buy-and-hold investment (8.73% p.a.) is that using the variables of Liu and
Mei (1992) (11.42% p.a.). In Australia, the passive investment (10.16% p.a.) is outperformed by the active strategy using financial and real estate factors (15.84% p.a.), as well as by the active strategy using the variables of Chan, Hendershott and Sanders (1990) (11.28% p.a.).

The models that outperform the buy-and-hold investment, do so even in the presence of transaction costs. Transaction costs are taken into account by calculating the amount that would render the active strategy’s profits equivalent to the buy-and-hold profits. As reported in Table 4, the costs associated with such strategies cover comfortably the average round-trip execution costs (30 basis points as estimated by Chan and Lakonishok 1993). Therefore, the active investment strategies provide economically significant outcomes.

The fractional cointegration analysis provides the following explanations for the trading results. As expected, the long-range dependence found in the U.S. and Australia between securitized real estate and the financial and real estate factors result in this model having the best trading outcomes. The presence of long memory also explains the good results obtained with the economic variables of Chan, Hendershott and Sanders (1990) in Australia. Finally, the performance of the economic variables of Liu and Mei (1992) in the U.K. may be explained by the estimated degree of cointegration and its confidence interval which suggest that in addition to short memory between securitized real estate and these variables, there could also be some long memory.

The differences in predictability between the U.S. and Australia, and the U.K., could be due to the structural differences of these markets concerning tax-transparency. REITs were only introduced in the U.K. in 2007, while the U.S. and Australia had REITs during the whole period studied. This result confirms a finding by Serrano and Hoesli (forthcoming) who find that securitized real estate returns are generally more predictable in countries with mature
and well established REIT regimes. On the other hand, the differences in the amount of leverage used by real estate companies across countries seem to have a limited impact on the predictability of their returns. Attempting to disentangle the effect of REIT legislation (tax-transparency), leverage, and portfolio composition on the predictability of securitized real estate returns would appear to be a fruitful area for future research, as would be an analysis of these factors or the linkages between securitized real estate and direct real estate (Pagliari, Scherer and Monopoli 2005).

6 Concluding Remarks

The debate concerning the economic variables to include in a forecasting model of asset returns is probably endless. An optimal model that remains robust through different time periods, countries, and asset classes, is hardly conceivable. For securitized real estate, an asset class often described as a hybrid asset (i.e., a hybrid of stocks, bonds and real estate) such a choice of variables may be bypassed. In this paper, we use financial and real estate factors as forecasting variables to proxy for the set of economic variables related to changing economic trends and business conditions that exert an effect on securitized real estate performance. The primary contribution of this paper was to determine whether such financial and real estate factors provided at least as good forecasts for securitized real estate returns as the commonly used economic variables. This was undertaken by identifying and describing the long-run nonlinear relations between securitized real estate and two sets of economic variables on the one hand, and between securitized real estate and financial and real estate factors on the other.

With fractional cointegration analysis, the paper identifies and characterizes the nonlinear relationships that exist between securitized real estate and the
three specifications tested. In fact, we find that the economic variables of Chan, Hendershott and Sanders (1990) generally have no long-run effects on securitized real estate as the process is mean reverting. There is some evidence that securitized real estate and the economic variables of Liu and Mei (1992) display short memory, but the strongest linkage is found with financial and real estate factors where a long memory process generally links securitized real estate to these variables.

More accurate securitized real estate return forecasts are obtained with financial and real estate factors than with economic variables in the U.S. and in Australia, while in the U.K., it is with the economic variables of Liu and Mei (1992) that the best forecasts are made. Such outcomes are economically significant as they continue to hold when transaction costs are taken into account. The trading results are also consistent with the long-range dependence found in the U.S. and Australia between securitized real estate and the financial and real estate factors, as well as with the short memory and possible long memory found in the U.K. between securitized real estate and the economic variables of Liu and Mei (1992).
References


## Table 1: Sets of Variables Examined

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Variable</th>
<th>Data Source or Measurement</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_t$</td>
<td>Inflation</td>
<td>Consumer price index</td>
</tr>
<tr>
<td>$TB_t$</td>
<td>Treasury-bill rate</td>
<td>3-month Treasury-bill rate in the U.S. and the U.K., and 3-month Interbank middle rate in Australia</td>
</tr>
<tr>
<td>$B_t$</td>
<td>Long-term government bonds</td>
<td>Datastream’s 10-year total return government bond index</td>
</tr>
<tr>
<td>$AAA_t$</td>
<td>Corporate AAA bonds</td>
<td>Citigroup’s corporate AAA/AA bond index</td>
</tr>
<tr>
<td>$BBB_t$</td>
<td>Corporate BBB bonds</td>
<td>Citigroup’s corporate BBB bond index</td>
</tr>
</tbody>
</table>

### Panel A: Raw Economic Series and Sources

- **Chan, Hendershott and Sanders (1990)**
  - $\Delta TS_t$: Change in term structure: $B_t - TB_t$
  - $\Delta RP_t$: Change in risk premium: $BBB_t - AAA_t$
  - $\Delta EI_t$: Change in expected inflation: $EI_{t+1} - EI_t$
  - $UI_t$: Unexpected inflation: $I_t - EI_t$

- **Liu and Mei (1992)**
  - $TB_t$: 3-month Treasury-bill rate in the U.S. and the U.K., and 3-month Interbank middle rate in Australia

### Panel B: Economic Variables

- Yield spread: $AAA_t - TB_t$
- Stocks dividend yield: Datastream’s stock’s dividend yield index
- REITs Cap. Rate: FTSE/NAREIT All REITs dividend yield index in the U.S. and GPR General dividend yield index in the U.K. and Australia

### Panel C: Financial and Real Estate Factors

- Stock factor: Datastream’s total return stock index
- Bond factor: Datastream’s 10-year total return government bond index
- Real estate factor: NCREIF Property Index (NPI) in the U.S., IPD index in the U.K., and Mercer’s Unlisted Property Fund Index (MUPFI) in Australia

### Notes:

For Australia the Treasury-bill rate is not available for the whole period so the Interbank 3-month middle rate is used. Their correlation over the shorter common time period for which both variables are available (1986Q2-2002Q2) is 0.97.

Investment grade bonds data are not available in the U.K. and Australia for the whole period, so these variables are proxied using U.S. data. The correlation between U.S. and U.K. AAA bonds is 0.75, while the correlation is 0.62 for BBB bonds. In Australia, these correlations are 0.79 and 0.48, respectively.

As done by Chan, Hendershott and Sanders (1990), expected inflation is calculated using Fama and Gibbons (1984), i.e., $EI_t = TB_{t-1} - \frac{1}{12} \sum_{s=t-1}^{t-12} [TB_{s-1} - I_s]$. 

\[\sum_{s=t-1}^{t-12} [TB_{s-1} - I_s].\]
Table 2: Summary Statistics, 1980-2008Q2 for the U.S. and 1987-2008Q2 for the U.K. and Australia (Quarterly Data)

<table>
<thead>
<tr>
<th></th>
<th>United States (%)</th>
<th>United Kingdom (%)</th>
<th>Australia (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Securitized Real Estate</td>
<td>Mean</td>
<td>3.12</td>
<td>2.08</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>7.37</td>
<td>10.50</td>
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<tr>
<td>Stocks</td>
<td>Mean</td>
<td>3.46</td>
<td>2.49</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>7.95</td>
<td>8.08</td>
</tr>
<tr>
<td>Bonds</td>
<td>Mean</td>
<td>2.28</td>
<td>2.06</td>
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<tr>
<td></td>
<td>Std. Dev.</td>
<td>4.78</td>
<td>3.60</td>
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<td>Direct Real Estate (Unsmoothed)</td>
<td>Mean</td>
<td>2.22</td>
<td>2.19</td>
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<tr>
<td></td>
<td>Std. Dev.</td>
<td>3.81</td>
<td>8.62</td>
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<tr>
<td>T-Bill</td>
<td>Mean</td>
<td>1.38</td>
<td>1.68</td>
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<tr>
<td></td>
<td>Std. Dev.</td>
<td>0.72</td>
<td>0.75</td>
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<tr>
<td>Yield Spread</td>
<td>Mean</td>
<td>1.01</td>
<td>0.19</td>
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<tr>
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<td>Std. Dev.</td>
<td>4.05</td>
<td>2.40</td>
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<td>Dividend Yield Stocks</td>
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<td>2.83</td>
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<td>Std. Dev.</td>
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<td>0.80</td>
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<td>Dividend Yield</td>
<td>Mean</td>
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<td>0.41</td>
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<tr>
<td>Change in Term Structure</td>
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<tr>
<td></td>
<td>Std. Dev.</td>
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<td>3.60</td>
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<tr>
<td>Change in Risk Premium</td>
<td>Mean</td>
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<td>0.08</td>
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<tr>
<td></td>
<td>Std. Dev.</td>
<td>1.19</td>
<td>1.15</td>
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<tr>
<td>Expected Inflation</td>
<td>Mean</td>
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<td>1.34</td>
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<tr>
<td></td>
<td>Std. Dev.</td>
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<td>0.65</td>
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<tr>
<td>Change in Expected Inflation</td>
<td>Mean</td>
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<td>-0.02</td>
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<td>Std. Dev.</td>
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<td>0.19</td>
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<tr>
<td>Unexpected Inflation</td>
<td>Mean</td>
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<td>-0.66</td>
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<tr>
<td></td>
<td>Std. Dev.</td>
<td>0.49</td>
<td>0.74</td>
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Table 3: Estimated Fractional Cointegration Coefficients

<table>
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<tr>
<td></td>
<td>d</td>
<td>95% Confidence Interval</td>
<td>d</td>
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<tr>
<td>United States</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>( \mu = 0.55 )</td>
<td>0.92</td>
<td>[0.22 1.62]</td>
<td>-0.28</td>
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<tr>
<td>( \mu = 0.575 )</td>
<td>0.94</td>
<td>[0.34 1.54]</td>
<td>-0.07</td>
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<tr>
<td>( \mu = 0.60 )</td>
<td>1.08</td>
<td>[0.43 1.72]</td>
<td>0.01</td>
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<tr>
<td>United Kingdom</td>
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<td>( \mu = 0.55 )</td>
<td>0.59</td>
<td>[-0.37 1.55]</td>
<td>-0.62</td>
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<tr>
<td>( \mu = 0.575 )</td>
<td>0.60</td>
<td>[-0.26 1.46]</td>
<td>-0.46</td>
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<tr>
<td>( \mu = 0.60 )</td>
<td>0.64</td>
<td>[-0.08 1.35]</td>
<td>-0.22</td>
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<tr>
<td>Australia</td>
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<td></td>
<td></td>
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<tr>
<td>( \mu = 0.55 )</td>
<td>0.31</td>
<td>[0.08 0.54]</td>
<td>-0.52</td>
</tr>
<tr>
<td>( \mu = 0.575 )</td>
<td>0.44</td>
<td>[0.01 0.88]</td>
<td>-0.39</td>
</tr>
<tr>
<td>( \mu = 0.60 )</td>
<td>0.49</td>
<td>[0.12 0.86]</td>
<td>-0.26</td>
</tr>
</tbody>
</table>

Notes:
This table shows the fractional cointegration coefficients estimated with equation (4), \( \ln(I_{\mu}(\omega_j)) = \alpha + \beta \ln(4\sin^2(\omega_j/2)) + \varepsilon_t \). Three sets of variables are considered: the ones used by Chan, Hendershott and Sanders (1990), those of Liu and Mei (1992), and financial and real estate factors. The table also reports the 95% confidence intervals. For the sample size function \( n = T^\mu \), we report results for \( \mu = 0.55, 0.575, \) and 0.60.
<table>
<thead>
<tr>
<th></th>
<th>United States</th>
<th>United Kingdom</th>
<th>Australia</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Annual Return (%)</td>
<td>Round-Trip Transaction Costs (bp)</td>
<td>Annual Return (%)</td>
</tr>
<tr>
<td>Chan, Hendershott and Sanders (1990) Variables</td>
<td>8.49</td>
<td>0</td>
<td>7.47</td>
</tr>
<tr>
<td>Liu and Mei (1992) Variables</td>
<td>13.44</td>
<td>0</td>
<td>11.42</td>
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<tr>
<td>Financial and Real Estate Factors</td>
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<td>302</td>
<td>5.92</td>
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<tr>
<td>Buy-and-Hold Investment</td>
<td>14.32</td>
<td></td>
<td>8.73</td>
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</tbody>
</table>

Notes: This table shows the annual returns on the active trading strategies with the three forecasting specifications, as well as the buy-and-hold strategy. Transaction costs which would render the active strategy equivalent to the passive one are also shown.