Forecasting EREIT Returns

Executive Summary. *This paper analyzes the role played by financial assets, direct real estate, and the Fama and French (1993) factors in explaining equity real estate investment trust (EREIT) returns and examines the usefulness of these variables in forecasting returns. Four models are analyzed and their predictive potential is assessed by comparing three forecasting methods: time varying coefficient (TVC) regressions, vector autoregressive (VAR) systems, and neural networks models. Trading strategies on these forecasts are compared to a passive buy-and-hold strategy. The results show that EREIT returns are better explained by models including the Fama and French factors. The VAR forecasts are better than the TVC forecasts, but the best predictions are obtained with neural networks and especially when they are applied to the model using stock, bond, real estate, size, and book-to-market factors.*

by Camilo Serrano*
Martin Hoesli**

The market capitalization of real estate investment trusts (REITs) in the United States has grown from $1.4 billion in 1978, to $15.9 billion in 1992, and to $438 billion in 2006.[1] Consequently, an increasing amount of research has been devoted to this asset class.[2] In particular, substantial focus has been placed on identifying the determinants of securitized real estate returns. Two currents have emerged from this literature. The first stream concentrates on economic and financial variables such as GDP, inflation, short-term interest rates, the term structure, dividend yields, capitalization rates, and price-earning ratios (Chan, Hendershott, and Sanders, 1990; and Chen, Hsieh, and Jordan, 1997). The second stream examines the linkages between securitized real estate returns and those of stocks, bonds, and real estate (Clayton and MacKinnon, 2001 and 2003; and Hoesli and Serrano, 2007).

It seems logical too to consider these two approaches in devising forecasting tools. A few authors have relied upon economic and financial variables for prediction purposes (Bharati and Gupta, 1992; Liu and Mei, 1992; Mei and Liu, 1994; and Brooks and Tsolacos, 2001 and 2003). Using such variables to model returns is appealing from a theoretical perspective as they impact supply and demand and ultimately asset prices. However, identifying the relevant variables and their impacts is not unproblematic for researchers. To date, no consensus has been reached concerning the best predicting variables.

Although securitized real estate has often been described as a hybrid of stocks, bonds, and real estate, no research has to date attempted to use this

*University of Geneva (HEC), Geneva 4, Switzerland or camilo.serrano@hec.unige.ch.

**University of Geneva (HEC and SFI), Geneva 4, Switzerland, University of Aberdeen (Business School), Aberdeen AB24 3QY, Scotland, UK, and Bordeaux Business School, Talence Cedex, France or martin.hoesli@hec.unige.ch.

hybrid nature for predicting returns on this asset class. This paper contributes to filling this void in the literature. By accepting the premise that equity REITs (EREITs) are investments whose underlying assets are stocks, bonds, and real estate, we are actually using aggregate proxies for the set of economic and financial variables that should be useful in forecasting EREIT returns. Hence, what differentiates this paper from past studies on securitized real estate forecasting is that it examines the possibility of making profitable forecasts based on the findings that securitized real estate is a hybrid asset.

The objectives of this paper are twofold. We first depict the ex post time-varying explanatory power that stock, bond, real estate, size, and book-to-market factors have on EREIT returns. Four models are considered: (1) the CAPM, (2) the CAPM with the Fama and French (1993) factors, (3) the Clayton and MacKinnon (2003) hybrid model, and (4) the Clayton and MacKinnon model with the Fama and French factors. In doing so, we also examine the beta behavior of these factors. We then turn to the more important aim of this paper, which is to examine which type of model is most useful for prediction purposes. We examine the forecasting ability of the four securitized real estate return-generating models by employing three forecasting methods: time varying coefficient (TVC) regressions, vector autoregressive (VAR) systems, and neural networks models. Forecasting accuracy is measured with traditional statistical criteria, as well as by comparing active investment strategies based on our forecasts to a passive buy-and-hold strategy. This enables us to determine not only which model specification is the most appropriate for securitized real estate forecasting, but also which forecasting technique makes the most accurate predictions.

EREIT returns are found to be positively related to stock, size, and book-to-market factors. Nevertheless, these relationships are quite volatile, with stocks and size being predominant until the early 1990s, while the book-to-market and size factors dominate thereafter. With bonds a generally positive but weak relationship is found, whereas with real estate, the relationship exhibits much variability and appears to be cyclical. The best forecasting tool is clearly neural networks, while the most appropriate model specifications are those including the Fama and French (1993) factors. Some of our forecasts are tradable, meaning that they outperform a passive investment strategy and could therefore be used profitably under real market conditions.

The paper is organized as follows. First, there is a review of the literature concerning securitized real estate's hybrid nature and the forecasting of its returns. Next, the data is presented and the methodology described. Finally, the results are discussed and the paper closes with some concluding remarks.

Literature Review

The notion that securitized real estate is a hybrid asset results from the fact that it is publicly traded, that the generally long-term fixed leases generate a fixed income, and that the underlying asset is real estate. Giliberto (1990), Gyourko and Keim (1992), and Mei and Lee (1994) find the presence of a common real estate factor linking the performance of securitized and direct real estate. The relation of securitized real estate with financial assets has also been analyzed and the evidence found about REIT returns being correlated with both stock and bond returns is compelling (Peterson and Hsieh, 1997; Karolyi and Sanders, 1998; and Ling and Naranjo, 1999). Recently, and at an international level, Hoesli and Serrano (2007) cover 16 countries and conclude that securitized real estate returns are generally positively associated with stock and direct real estate returns, but negatively related to bond returns.

With the idea of further decomposing the stock market factor, additional efforts have been deployed to better characterize the importance of stock capitalization and the value/growth classification. Various large cap, small cap, value, and growth representations have been used for that matter, as well as the size and book-to-market factors of Fama and French (1993). Hamelink and Hoesli (2004) find size to have a negative impact on returns and the value/growth factor to have a substantial effect on returns while being volatile (see also Anderson, Clayton, MacKinnon, and

Sharma, 2005). Consistent with those studies, Chiang, Lee, and Wisen (2004 and 2005) find the three-factor model of Fama and French to be more appropriate in explaining the variation of EREIT returns than the single-factor model of Sharpe (1964).

Much research has also examined the time-varying nature of these linkages. Glascock, Lu, and So (2000) find that before 1992, REITs were cointegrated with bonds and inflation, while after 1992 they were cointegrated with stocks and even more so with small caps. The similarity of securitized real estate with small caps is also acknowledged by Clayton and MacKinnon (2003). They report that REITs went from being driven by the same economic factors as large caps in the 1970s and 1980s, to being more strongly related to both small caps and real estate-related factors in the 1990s. Anderson et al. (2005) distinguish between value and growth small cap stocks and find that REITs behave more like small cap value stocks than like small cap growth stocks or large cap stocks.

Thus far, the literature covered has referred to the past, but some researchers have also addressed forecasting issues. Early studies on the predictability of real estate security returns yield very promising results for forecasting purposes. Liu and Mei (1992), for instance, find that EREITs are more predictable than stocks and bonds, while Bharati and Gupta (1992) conclude that active investment strategies outperform passive ones, even in the presence of transaction costs. However, Li and Wang (1995) argue that there is no evidence to support that REIT returns are more predictable than the returns of other stocks. More recently, various aspects of forecasting have been addressed; namely, the three major stages involved in forecasting: choosing the inputs, selecting the methodology, and finding an appropriate evaluation measure. The inputs that have been used for securitized real estate forecasting comprise various economic and financial variables thought to contain useful information about the future business activity and market expectations. The forecasting techniques that have been employed include the long-term mean, ARMA, VAR, and neural network models. Finally, the evaluation metrics that have been used consist of several statistical criteria, as well as trading profits derived from trading strategies conceived with the forecasts.

Brooks and Tsolacos (2001) examine the predictability of securitized real estate returns in the United Kingdom by using a number of time series techniques. They conclude that for a short forecasting horizon, a VAR model that incorporates financial spreads exhibits better out-of-sample forecasting performance than univariate time series models. Such forecasts are turned into a trading rule, but they do not generate excess returns over a buy-and-hold strategy once transaction costs are accounted for. Brooks and Tsolacos (2003) compare the predictability of the autoregressive moving average (ARMA), VAR, and neural network models in five European countries. Within a VAR framework, they demonstrate that the guilt-equity yield ratio[3] is generally a better predictor than the term structure or the dividend yield. Overall, they find that while no single technique is universally superior, the neural network model generally makes the most accurate predictions for one-month horizons. Similarly, Ellis and Wilson (2005) apply neural network modeling techniques to the Australian property stock sector to construct a variety of value portfolios. Based both on nominal and risk-adjusted returns, the evidence appears overwhelming that portfolios constructed by means of neural networks are quite capable of outperforming the market on a consistent basis.

The usefulness of various forecasting techniques has also been ascertained in the direct real estate literature, mostly with housing data. Results are somewhat conflicting. Nguyen and Cripps (2001) and Limsombunchai, Gan, and Lee (2004) believe that neural networks perform better than hedonic price models for house price prediction. However, Worzala, Lenk, and Silva (1995) and Lenk, Worzala, and Silva (1997) argue that this type of appraisal might lead to significant estimation error costs; furthermore, that results are inconsistent between packages and between runs, and that it is a highly time-consuming estimation method. Brown, Song, and McGillivray (1997) suggest that in the U.K. housing market, a time-varying coefficient regression outperforms forecasts from constant parameter error correction models (ECMs), VAR systems, and an autoregressive regression. In the U.S., Crawford and Fratantoni (2003) find that even if regime-switching models fit the data better than autoregressive integrated moving average (ARIMA) or generalized autoregressive conditional heteroscedasticity (GARCH) models, they may overfit the data in small samples. They therefore conclude that simpler time series models perform as well or better in out-of-sample tests. Similarly, Guirguis, Giannikos, and Anderson (2005) provide strong empirical evidence in favor of utilizing the rolling GARCH model and the Kalman filter with an autoregressive presentation (KAR) for the parameters' time variation. In the Finnish office market, Karakozova (2004) uses a regression model, an ECM, and an ARIMAX to forecast office capital returns in Helsinki. The latter technique provides the best forecasting tool when it incorporates past values of capital growth and growth in service sector employment and in the gross domestic product.

Finally, our review on predictability ends by taking a look at market efficiency.[4] The reason for doing so is that if markets are efficient, no information or analysis can be expected to result in outperformance of an appropriate benchmark. This means that if markets are efficient, the usefulness of forecasting returns might be limited as it becomes more difficult to profit from the forecasts. Empirical work on market efficiency depends on the subset of information used to determine if prices fully reflect the information available. Weak-form market efficiency is concerned with historical prices or returns, semi-strong-form market efficiency deals with the speed of price adjustment to publicly available information such as financial report releases, company announcement, macroeconomic data releases, etc., while strong-form market efficiency examines whether any investor has privileged access to information relevant for price formation.

The evidence concerning the efficiency of the securitized real estate market is mixed, with authors such as Kleiman, Payne, and Sahu (2002) reporting that the market is efficient, while Kuhle and Alvayay (2000) have reached the opposite conclusion. There are some signs too of the increased efficiency of the market. Such a result is obtained by Jirasakuldech and Knight (2005) on the basis of autocorrelation tests, variance ratio tests, and nonparametric runs tests. There has also been indirect evidence on the efficiency issue. Brooks and Tsolacos (2001) and Nelling and Gyourko (1998) support the weak-form market efficiency hypothesis by examining the predictability of EREIT returns and finding no evidence of unexploited arbitrage opportunities once transaction costs have been taken into account. However, Cooper, Downs, and Patterson (2000) examine the predictability of REIT returns for evidence of information-based trading and their results appear to contradict the strong-form hypothesis. They find that large absolute magnitude price changes accompanied by high volume will reverse but this pattern is stronger during low-volume periods. Their interpretation is that periods with high volume contain a greater proportion of private information, which leads to less predictable reversals in portfolio returns, while the reverse applies for low trading volume. This means that private information is relevant for price formation. Overall, the results on market efficiency are mixed, and hence predictability in returns could be expected.

Data

The data were obtained from *Thomson Datastream* except for the real estate series and the Fama and French (1993) factors. All indices used are quarterly total return indices for the period 1978–2006.[5] For securitized real estate, the FTSE NAREIT EREIT series is chosen.[6] Datastream's total market index is used for stocks, and the Merrill Lynch's 7–10 year government bond index is used for bonds. As a risk-free rate, the Euro-Currency three-month middle rate is retained. The size and book-to-market factors have been provided by Kenneth French. Finally, the NCREIF Property Index (NPI) is used for direct real estate. Real estate returns are unsmoothed using the approach proposed by Geltner (1993). Hence, the unsmoothed index is obtained as follows: $r_t^u = (r_t^* - ar_{t-1}^*)/(1 - a)$, where r_t^u is the unobserved true return, r_t^* is the return resulting from the observed appraised value, and a is the unsmoothing parameter. To avoid setting the unsmoothing parameter arbitrarily, it is assumed that the real estate series follows an AR(1) process. Thus, α is defined as the estimated β coefficient in the following regression: $r_t^* = \alpha + \beta r_{t-1}^*$.

Descriptive statistics and the correlation matrix are displayed in Exhibit 1. Mean quarterly returns are highest for EREITs, followed by stocks, real estate, and bonds. In terms of volatility, their ordering from most to least volatile is: stocks, EREITs, bonds, and real estate. Regarding the Fama and French (1993) factors, the book-to-market factor is twice as large in magnitude as the size factor, but the volatility of the two factors is relatively similar. In the correlation matrix, most correlations are low; the highest correlation being that between EREITs and stocks (0.53).[7]

Since VAR systems can only be used with stationary series, the stationarity of all raw series is examined by means of two unit root tests: the Augmented Dickey-Fuller (ADF) and the Phillips-Peron (PP) tests. The former is a parametric test based on the estimation of an AR(p) model, in which the null hypothesis of a unit root (i.e., that coefficients of the lagged dependent variables are unitary) is tested against the alternative that they are strictly less than one (i.e., stationary). The PP test is similar to the ADF test, but it is based on an AR(1) model and uses a nonparametric method to control for serial correlation. Hence, it is harder to reject the null hypothesis of non-stationarity with the ADF test than with the PP test. All of our raw series are stationary, except for direct real estate with the ADF test. Therefore, all of the series used for the VAR systems are I(0) except for the real estate index, which is I(1).

Methodology

The first goal is to determine the appropriateness of the one-factor model of Sharpe (1964) and of the stock, bond, and real estate factors' model of Clayton and MacKinnon (2003) in explaining past securitized real estate returns and additionally to see if the Fama and French (1993) factors add any explanatory power to these models. Hence, we have four models. The other aim of this paper is to analyze which of these four models performs better for out-of-sample forecasts of EREIT returns. For this purpose, we use three forecasting techniques.

Models Employed

The past behavior of the various factors included in each model is examined through their betas. Betas are estimated using five-year rolling ordinary

Exhibit 1

Summary Statistics and Correlation Matrix of all the Raw Series (Quarterly Data for the Period 1978–2006)

	EREITS	STOCKS	BONDS	DIRECT	DIRECT UNSMOOTHED	SMB	HML	Rf
Summary Statistics								
Mean (%)	3.86	3.55	2.19	2.45	2.48	0.59	1.25	1.69
Std. Dev. (%)	6.95	7.87	4.52	1.70	4.14	5.10	6.15	0.92
Maximum (%)	22.74	22.88	18.51	6.19	12.73	12.71	25.12	4.72
Minimum (%)	−14.55	−22.04	−9.24	−5.33	−17.37	−10.28	−18.82	0.26
Correlation Matrix								
EREITS	1.00	0.53	0.25	0.03	0.12	0.50	0.02	−0.01
STOCKS	0.53	1.00	0.14	−0.05	−0.04	0.34	−0.53	0.05
BONDS	0.25	0.14	1.00	−0.14	−0.15	−0.14	0.09	0.21
DIRECT	0.03	−0.05	−0.14	1.00	0.71	−0.06	0.02	0.28
DIRECT UNSMOOTHED	0.12	−0.04	−0.15	0.71	1.00	0.02	0.04	0.01
SMB	0.50	0.34	−0.14	−0.06	0.02	1.00	−0.23	−0.04
HML	0.02	−0.53	0.09	0.02	0.04	−0.23	1.00	0.01
Rf	−0.01	0.05	0.21	0.28	0.01	−0.04	0.01	1.00

Note: The number of observations is 116 (115 for the unsmoothed real estate series).

least squares (OLS) regressions for the four models under study. To examine any potential multicollinearity, we look at the correlations between the explanatory variables. As the correlations are low (between −0.53 and 0.34), we do not orthogonalize the variables before estimating the equations. The four models estimated are the following.

Model 1: Capital Asset Pricing Model (CAPM) of Sharpe (1964):

$$r_{EREIT,t} = \alpha + \beta_S r_{S,t} + u_t, \tag{1}$$

where $r_{EREIT,t}$ and $r_{S,t}$ are the total excess returns for quarter t of EREITs and stocks, respectively.

Model 2: CAPM with the Fama and French (1993) Factors:

$$\begin{aligned} r_{EREIT,t} = \alpha &+ \beta_S r_{S,t} + \beta_{SMB} SMB_t \\ &+ \beta_{HML} HML_t + u_t, \end{aligned} \tag{2}$$

where SMB_t is the difference between the returns of portfolios composed of small and large capitalization stocks for quarter t, and HML_t is the difference between the returns of portfolios composed of stocks with high and low book-to-market ratios.

Model 3: Clayton and MacKinnon (2003) Hybrid Model:

$$r_{EREIT,t} = \alpha + \beta_S r_{S,t} + \beta_B r_{B,t} + \beta_{RE} r_{RE,t} + u_t, \tag{3}$$

where $r_{B,t}$ and $r_{RE,t}$ are the total excess returns for quarter t of government bonds and direct real estate, respectively.

Model 4: Clayton and MacKinnon (2003) Model with the Fama and French (1993) factors:

$$\begin{aligned} r_{EREIT,t} = \alpha &+ \beta_S r_{S,t} + \beta_B r_{B,t} + \beta_{RE} r_{RE,t} \\ &+ \beta_{HML} HML_t + \beta_{SMB} SMB_t + u_t. \end{aligned} \tag{4}$$

After depicting the behavior of the betas in the different models and determining the explanatory power of each specification, we apply three forecasting techniques to each model in order to determine the model and the forecasting technique that are most appropriate for predicting EREIT returns, that is, if returns are indeed predictable with these variables. The three forecasting methodologies applied are: TVC regression, VAR system, and neural networks model.[8]

Forecasting Techniques

TVC Forecasting. With the time-varying coefficient (TVC) regression, we aim to model EREIT returns by using time-varying coefficients for each factor in each model. In order to make one quarter ahead forecasts, a rolling window of 20 quarterly observations is used for in-sample parameter estimation. Each new window shifts the sample by one observation, re-estimates the parameters, and produces a new forecast until the whole sample is exhausted. The time-varying regression used is:

$$r_{EREIT,t} = \beta_0 + \beta X_{t-1} + u_t, \tag{5}$$

where X_{t-1} is a vector of lagged explanatory variables that depend on the model being implemented (Models 1 through 4), β is a vector with the respective estimated coefficients, and u_t is the vector of innovations that are assumed to be mutually uncorrelated and independent of the explanatory variables.

VAR Forecasting. The vector autoregressive (VAR) system is a generalization of the univariate autoregressive (AR) models whose objective is to capture the evolution and interdependencies between multiple time series. The VAR system estimated is:

$$r_{EREIT,t} = \beta_0 + \sum_{i=1}^{n} \beta_i Y_{t-i} + u_t, \tag{6}$$

where Y is the vector of variables included in the system for each of the four models and i represents the number of lags of each variable in each equation determined by using Akaike's and Schwarz's Bayesian information criteria. The optimal number of lags for each variable used in the VAR models is determined by choosing the specification with lowest AIC and SBC values. The longest specification tested is arbitrarily set to include a year, hence, four quarterly lags. Both criteria lead to an optimal number of lags of one for all the variables.

Therefore, the main difference between the VAR and TVC representations is that the former includes the first lag of EREIT returns as an explanatory variable.

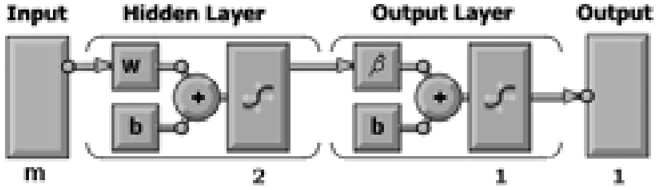
Neural Networks Forecasting. Neural networks are models that simulate how the human brain works. We could think of the models as an impulse-response mechanism constructed of several nodes (neurons) and several layers. As shown in Exhibit 2, the model employed here is known as a single hidden layer feed-forward neural network. Its structure consists of three layers, the inputs (akin to regressors), that are connected to the output(s) (the regressand) via a hidden or intermediate layer. The connection between the input and hidden layers is done through a hyperbolic tangent function that allows the network to account for nonlinearities. Econometrically, the problem reduces to estimating the "synaptic" weights or connection strengths between the layers. The neural network model can be written as:

$$r_{EREIT,t} = \sum_{j=1}^{N} \beta_j \varphi \left(\sum_{i=1}^{m} w_{ij} Z_{i,t-1} + b_j \right) + u_t, \quad (7)$$

where the number of hidden units in the intermediate layer is N, m is the number of inputs, Z_i are the inputs, β_j represents the hidden to output weights, w_{ij} the input to hidden weights, b_j is the "bias" term (akin to the constant term in a regression), and φ is a hyperbolic tangent function. A suitable network structure is determined for the neural networks model by using the same lags as in the VAR model as inputs, therefore, constituting a nonlinear specification of the VAR. One hidden layer with two neurons is used based on Hornik, Stinchocombe, and White (1989), who conclude that a single hidden layer network possesses the universal approximation property. This means that they can approximate any nonlinear function to an arbitrary degree of accuracy provided a sufficient number of hidden units are used.

Exhibit 2

Neural Network Architecture



Source: MATLAB 7.3.0 (R2006b)

The network is trained with the Levenberg-Marquardt optimization algorithm, which uses an iterative approach that locates the minimum of a function expressed as the sum of squares of nonlinear functions. This algorithm, which behaves as a combination of the steepest descent method and the Gauss-Newton method, has become a standard technique used in neural networks. It is a robust algorithm that finds a solution whether the starting point is far or not from the minimum.[9] Data are normalized to the range [−1,1] and the sample is divided into training, validation, and testing sub-samples. Training uses 40% of the sample and validation as well as testing take 30% each. The training sub-sample is used for adjusting the weights according to the network's error. Since the results vary between runs due to the random initialization values of the network, we choose networks with a high R^2 in the training sub-sample. The validation sub-sample serves to measure the network's generalization ability and stops the training once the mean squared error (MSE) starts increasing. This is to avoid overtraining. Finally, the testing sub-sample provides an out-of-sample or independent measure of the network's performance during and after training.

Assessing Performance. In a first instance, the forecasts produced by the different models are evaluated using the following traditional statistical loss functions:[10]

Mean Error (ME): It denotes the bias, but might result in a low ME if large positive and negative forecast errors cancel themselves.

$$ME = \sum_{t=T+1}^{T+h_t} (\hat{y}_t - y_t)/h. \quad (8)$$

Root Mean Squared Error (RMSE): It is an easily interpreted statistic since it has the same units as the forecast. It provides a quadratic loss function that avoids positive and negative errors to cancel.

$$RMSE = \sqrt{\sum_{t=T+1}^{T+h_t} (\hat{y}_t - y_t)^2 / h}. \quad (9)$$

Mean Absolute Error (MAE): It is generally used as a relative measure to compare forecasts for the same series across different models.

$$MAE = \sum_{t=T+1}^{T+h_t} |\hat{y}_t - y_t| / h. \quad (10)$$

Directional Accuracy: It measures the percentage of times that the return's sign is predicted correctly.

$$Sign(\hat{y}_t - y_{t-1}) = Sign(y_t - y_{t-1}). \quad (11)$$

Theil's U^2 Inequality Coefficient: Based on the RMSE, we calculate two different U^2 statistics by changing the base (denominator). The first U^2 statistic is calculated as the ratio of the RMSE from a forecasting model to the RMSE of the "naïve" model. The naïve model assumes that prices will not change, therefore the forecast at time t is simply the actual price at $t - 1$. This allows us to compare between the three forecasting methodologies. Values of U^2 greater than one entail that the forecasting technique is worse than the naïve model. The closer the U^2 value is to zero, the better the forecasting technique.

$$U_t^2 = \sum_{i=1}^{n_t} \sqrt{(\hat{y}_t - y_t)^2} \bigg/ \sum_{i=1}^{n_t} \sqrt{(y_t - y_{t-1})^2}. \quad (12a)$$

The second U^2 statistic is calculated as the ratio of the RMSE from a forecasting model to the RMSE of the one-factor model. Setting the CAPM as the base allows us to compare between the four models. Values of U^2 greater (lower) than one entail that the model used is worse (better) than the CAPM. The closer the U^2 value is to zero, the better the model.

$$U_t^2 = \sum_{i=1}^{n_t} \sqrt{(\hat{y}_t - y_t)^2} \bigg/ \sum_{i=1}^{n_t} \sqrt{(\hat{y}_{CAPM,t} - y_{CAPM,t})^2}. \quad (12b)$$

Statistical criteria such as mean errors, root mean squared errors, mean absolute errors, and so forth, allow us to assess to some extent the quality of forecasts. Nevertheless, a more pragmatic evaluation of a forecast is the actual feasibility of its use to reap abnormal profits.[11] Therefore, we construct an active trading strategy and compare it to a passive buy-and-hold investment on the EREIT index. Supposing that an investor takes a long position either on EREITs or on the risk-free asset (Euro-Currency three-month middle rate), the following trading rule is applied. If EREIT return forecasts are higher than the risk free assets' long-term mean, the investor will go long on EREITs, otherwise the investor will go long on the risk-free asset. The reason for using statistical criteria as well as a trading strategy is to see if the conclusions coincide. If we did not reach the same conclusions, we suggest that financial forecasts are evaluated with trading strategies because this performance metric is what ultimately interests portfolio managers.

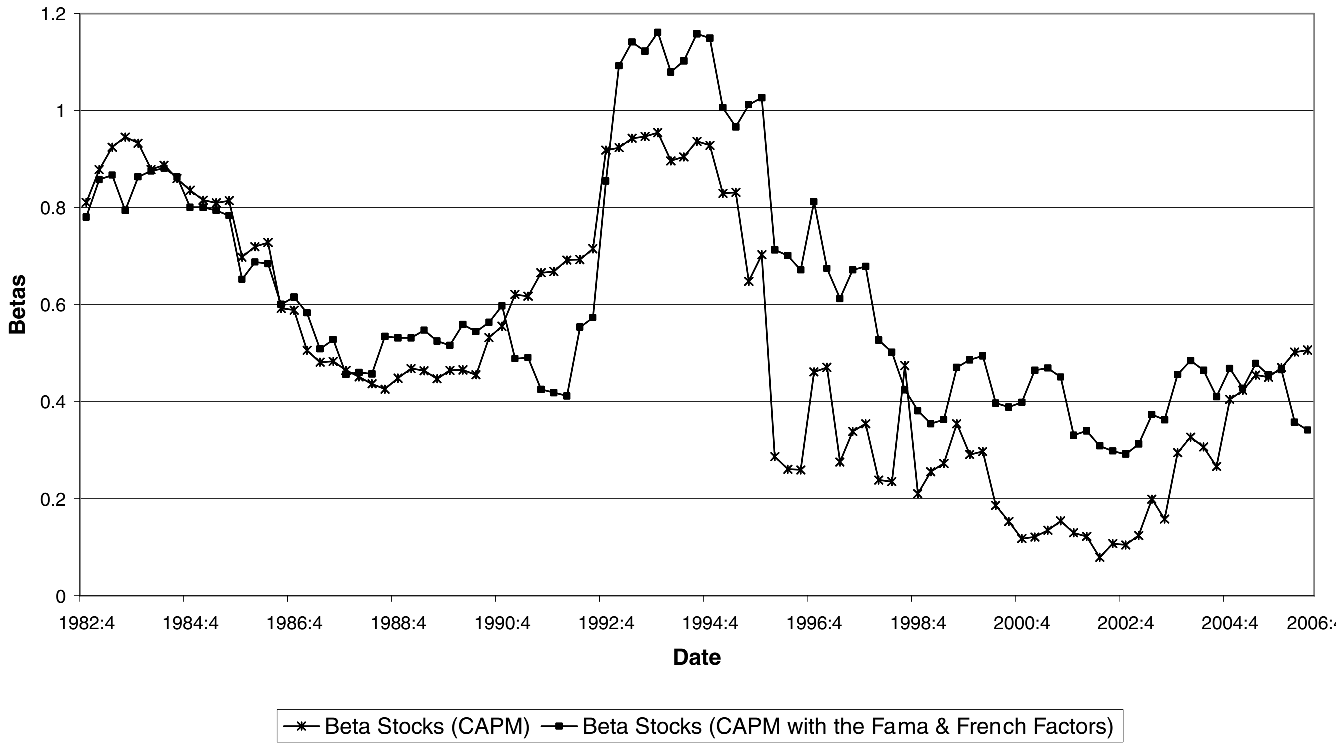
The impact of transaction costs in the trading strategies is taken into account by performing sensitivity analyses. Since not all investors face the same transaction costs, a sensitivity matrix is constructed to show the impact of "round-trip" costs ranging from 0% to 0.8% with 0.1% increments. The range of transaction costs chosen is in accordance with the study of Berkowitz, Logue, and Noser (1988) where they estimate "round-trip" transaction costs on the NYSE of 0.48% of the amount of the trade.

Empirical Results

Models' Results

As can be seen in Exhibit 3, adding the size and book-to-market factors to the market model does not alter the behavior of the stock market beta considerably. The betas estimated with the two models have a correlation coefficient of 0.80. With respect to the magnitude, a more pronounced hike of the stock beta in the three-factor model is observed in the beginning of the 1990s. This effect persists for the rest of the period and results in a shifted,

Exhibit 3
Five-Year Rolling Stock Beta Coefficients: 1978–2006



slightly higher beta for the three-factor model than for the one-factor model. The stock beta coefficients fluctuate between two ranges. Until the beginning of the 1990s, the range is between [0.4, 1.2] whereas, thereafter, the range drops to [0.1, 0.5]. An overall downward trend in the betas is observed during the whole period except for a hike in the early 1990s and since the start of the new millennium.

Khoo, Hartzell, and Hoesli (1993) and Hoesli and Serrano (2007) document decreasing betas thoroughly. Nevertheless, Chiang et al. (2005) study a similar period and find that when the three-factor model is used, as opposed to the one-factor model, stock market betas remain unchanged over time. We find that the reason for this discrepancy is explained by the frequency of the data used. We reproduce the results of Chiang et al. using monthly data but find that the same conclusions do not hold when quarterly data are employed. Since the stability of the betas using the three-factor model is subject to the frequency of the data used, it seems worthwhile to include other variables in the model. Given that the direct real estate data are only available at the quarterly frequency, we use quarterly data.

Exhibit 4 and Exhibit 5 illustrate the bond and real estate betas, respectively. Both figures depict two estimations of the betas, one with the stock, bond, and real estate factors model, and the other with the five-factor model that adds the size and book-to-market factors to the previous specification. For the bond factor, the estimations with the two models are very similar throughout the whole period (correlation of 0.82) except for the years 2002 and 2003 when the bond beta estimated with the more parsimonious model falls drastically and then rises vigorously, getting back in line with the five-factor model by late 2003. Bond betas are generally positive but small and have experienced much volatility since the beginning of the millennium. Real estate betas exhibit much variability

Exhibit 4

Five-Year Rolling Bond Beta Coefficients: 1978–2006

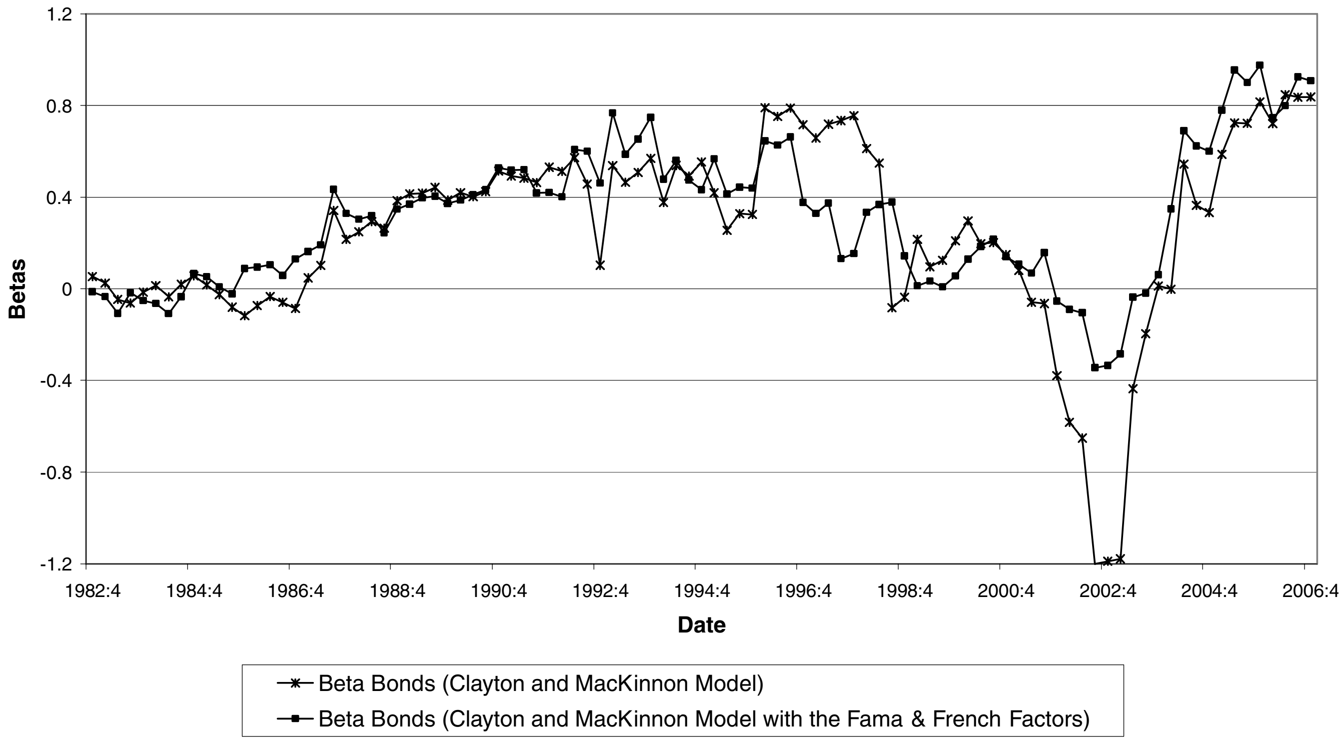
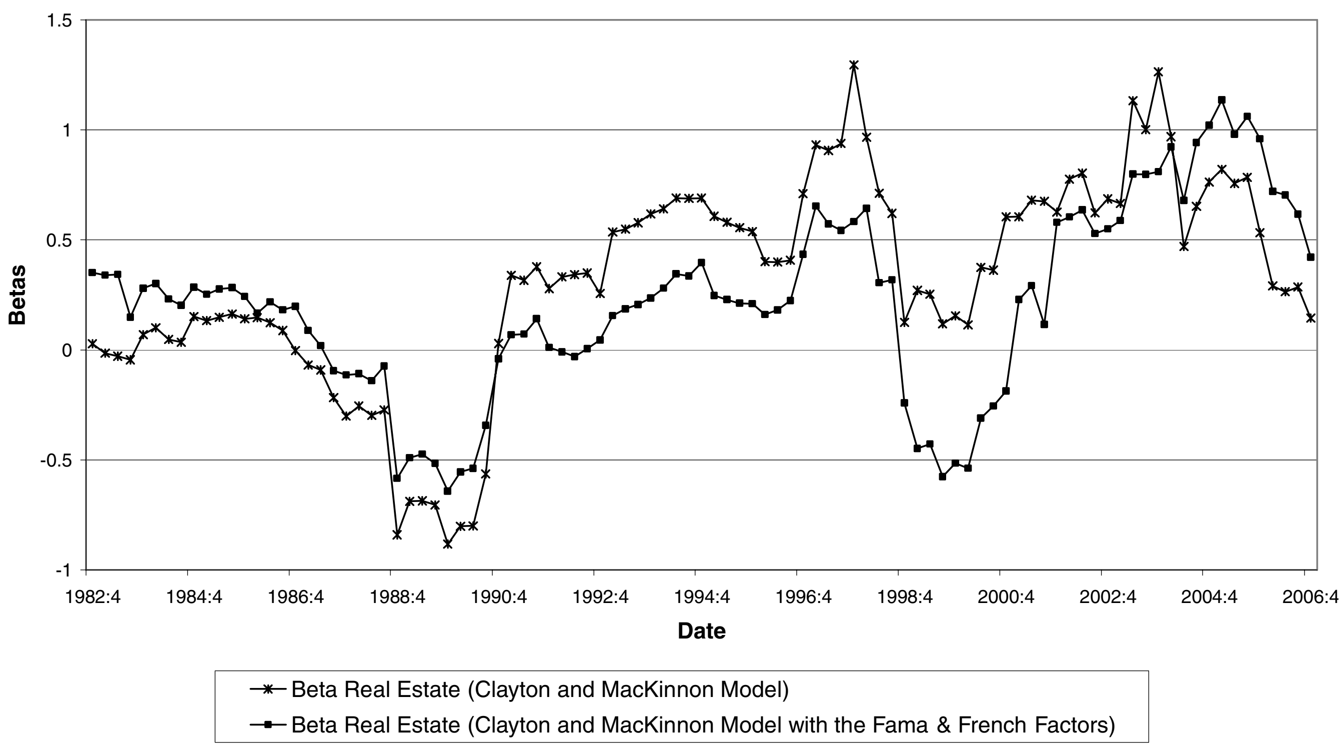


Exhibit 5

Five-Year Rolling Real Estate Beta Coefficients: 1978–2006



over the period and appear to be cyclical. The two models yield fairly similar real estate beta estimations over the whole period (correlation of 0.74) except from 1998 through 2001 when the estimations lie considerably lower for the model including the Fama and French (1993) factors.

The five-factor model comprising all the factors under study is shown in Exhibit 6. Overall, the findings reveal that EREIT returns are positively related to stock, size, and book-to-market factors. Nevertheless, these relationships are quite volatile, with stocks and size being predominant until the early 1990s, while the book-to-market and size factors dominate thereafter. This finding is consistent with the growing consensus that real estate securities behave like small cap value stocks (Glascock et al., 2000; Clayton and MacKinnon, 2001 and 2003; and Anderson et al., 2005). With bonds, a generally positive but weak relationship is found, whereas with real estate, the relationship exhibits much variability and seems to be cyclical. As in Clayton and MacKinnon (2003), we find that in the 1990s REITs became more linked with real estate-related factors; however, we posit that this is not a generalized tendency but rather a result of the real estate cycle.

The explanatory power of the four models decreased considerably over the period (Exhibit 7). For the CAPM and the Clayton and MacKinnon (2003) model, it dropped severely from around 75% to 15%.[12] The R^2 of the two models including the size and book-to-market factors did not suffer as strongly, but the range still dropped from approximately [0.5, 0.85] to [0.35, 0.65]. These results highlight the important role played by the Fama and French (1993) factors through time. Whereas these factors do not add substantially to the models' explanatory power at the beginning of the time period, they limit the loss in R^2 in the latter part of the period. Since the beginning of the millennium, the explanatory power of the four models is converging to similar levels (i.e., to around 50%).

Forecasting Results

Exhibit 8 reports the prediction accuracy of the four models using the three forecasting techniques.

Exhibit 6
Five-Year Rolling Beta Coefficients of the Clayton and MacKinnon Model with the Fama and French Factors: 1978–2006

Exhibit 7
Explanatory Power of the Four Models through Time

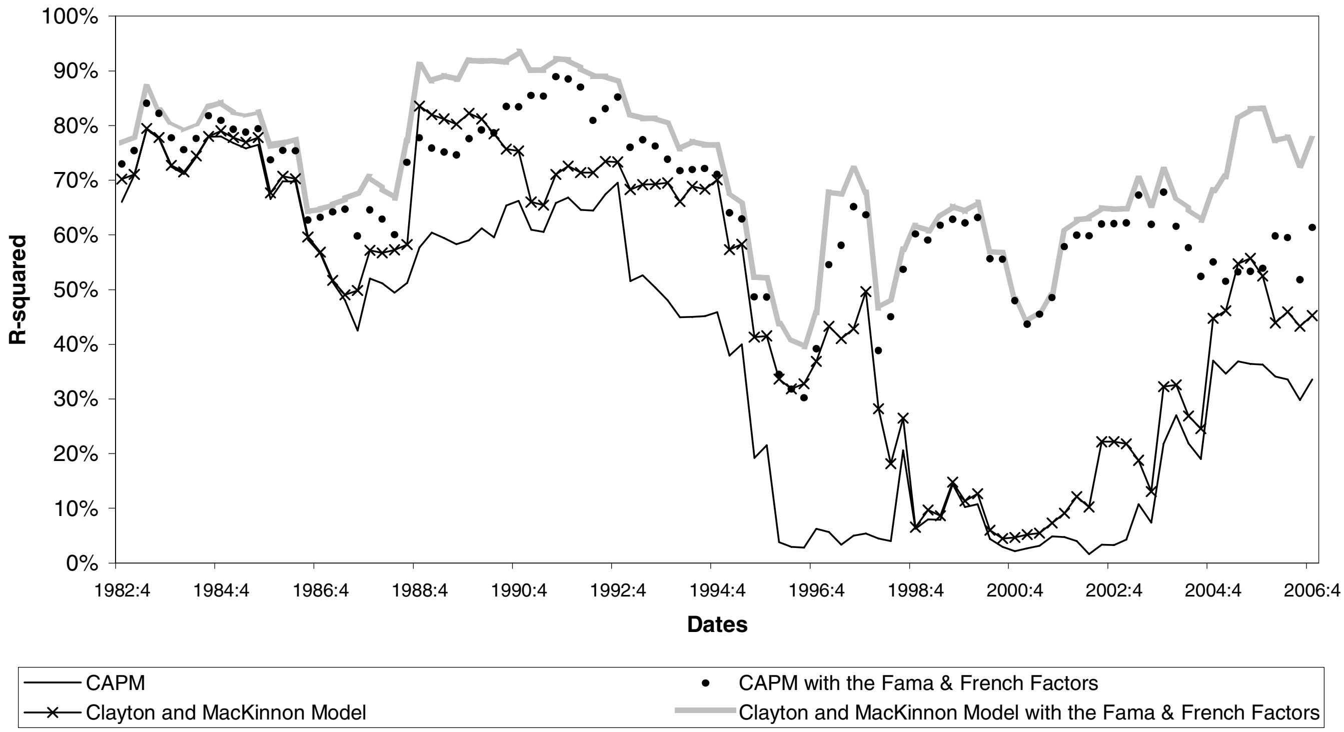


Exhibit 8
Forecasting Accuracies

	ME	RMSE	MAE	Sign	Theil's U^2 Statistic[a]	Theil's U^2 Statistic[b]
TVC						
Model 1	**−0.0070**	**0.0789**	**0.0680**	**0.6857**	**0.7975**	**1.0000**
Model 2	−0.0092	0.0954	0.0805	0.6286	0.9444	1.1842
Model 3	−0.0078	0.0837	0.0708	**0.6857**	0.8307	1.0416
Model 4	−0.0078	0.0996	0.0838	0.5143	0.9841	1.2339
VAR						
Model 1	**−0.0071**	**0.0667**	**0.0571**	0.6857	**0.6703**	**1.0000**
Model 2	−0.0075	0.0689	0.0599	**0.7143**	0.7026	1.0482
Model 3	−0.0095	0.0684	0.0587	0.6286	0.6894	1.0285
Model 4	−0.0092	0.0713	0.0620	0.6857	0.7279	1.0859
Neural Networks						
Model 1	−0.0072	0.0680	0.0600	0.6571	0.7039	1.0000
Model 2	−0.0048	0.0575	0.0435	0.7714	0.5103	0.7249
Model 3	−0.0043	0.0651	0.0576	0.7429	0.6757	0.9599
Model 4	**0.0027**	**0.0436**	**0.0345**	**0.8571**	**0.4049**	**0.5752**

Notes: Numbers in bold indicate the best model within a forecasting technique. Shaded numbers indicate the best model and forecasting technique.
[a] Base: "naïve" model
[b] Base: CAPM

Overall, neural network forecasts made with the five-factor model turn out to be the most accurate of all under all of the evaluation criteria. The first U^2 statistic is clear in determining that VAR forecasts perform better than those made with TVC. It is also clear in stating that neural network forecasts are superior to VAR forecasts when the Fama and French (1993) factors are used to make the predictions. Since in our case the neural network models used are nonlinear representations of the VAR systems, it is not surprising that the former technique outperforms the latter. Albeit Brooks and Tsolacos (2003) use economic and financial factors as their predicting variables, they also find that neural networks models generally produce the most accurate predictions.

According to all the evaluation metrics except for directional accuracy, the best TVC and VAR forecasts are those made with the one-factor model. The second U^2 statistic is greater than one for the three models that are compared with the CAPM. This would suggest that the CAPM is the best model. However, within the neural network forecasts, those made by the five-factor model outperform the forecasts made by the other models with respect to all the evaluation criteria. More so, the second U^2 statistic shows that the three models outperform the one-factor model when neural networks are employed. This means that when nonlinearities are taken into account in the forecasting technique, the most appropriate model is no longer the CAPM but the Clayton and MacKinnon (2003) model with the Fama and French (1993) factors. A possible explanation for this is that since TVC and VAR forecasts are linear, they will only identify the most straightforward relationships. Since EREITs have a strong stock component, it is not surprising that the CAPM is the best model with these techniques. On the other hand, nonlinear specifications such as neural networks are best suited when other and somewhat more subtle factors are also taken into account.

Trading Strategies on the Forecasts

An important result of this study is that most of our active trading strategies outperform the buy-and-hold investment (Exhibit 9). When neural networks forecasts are carried out on the five-factor model, an initial investment of \$1,000 would amount to \$4,936 with round-trip transaction costs as high as 80 basis points and to \$5,613 in the absence of transaction costs by the end of the 35 quarters over which the out-of-sample forecasts were performed. On the other hand, a passive buy-and-hold investment would be worth \$3,230. This means that some of the models and forecasting techniques analyzed are tradable even in the presence of transaction costs. The implications of these results with respect to market efficiency are as follows. The weak-form market efficiency hypothesis states that investors cannot consistently obtain abnormal returns simply by looking at universally available information. That is, security prices cannot be consistently forecasted from current and past price and market information. The results imply that asset returns may be forecasted and thus provide some evidence of violation of market efficiency.

Interestingly, the trading strategy results do not coincide entirely with the conclusions reached with statistical criteria. We therefore agree with Gerlow, Irwin, and Liu (1993) in the sense that only by comparing an active investment strategy to a passive one, can we fully understand if the predictions are useful or not. In our view, financial forecasts should not be evaluated with statistical criteria, but rather with financial indicators derived from trading strategies. This would make more sense for portfolio managers as the real impact of the forecasts can be clearly established. The only TVC forecasts that perform better than the buy-and-hold investment are those made with the Clayton and MacKinnon (2003) model but with transaction costs less than 30 basis points. The VAR forecasts beat the passive strategy with all the models except with the Clayton and MacKinnon model when transaction costs are higher than 10 basis points. Neural network forecasts achieve better results than the passive investment strategy with the four models for all transaction cost levels considered. It also proves to be better than the other two forecasting techniques. The best two forecasts are obtained when neural networks are applied to the two models that include the Fama and French factors. Overall, the best forecasts are obtained with the five-factor model, and the most profitable forecasting technique is neural networks.

Exhibit 9
Trading Strategies

	Model 1		Model 2		Model 3		Model 4	
TRANS. COSTS	NET WEALTH	TRANS. COSTS	NET WEALTH	TRANS. COSTS	NET WEALTH	TRANS. COSTS	NET WEALTH	TRANS. COSTS
Panel A: TVC								
0.00%	2791	0	3213	0	**3333**	0	2148	0
0.10%	2749	42	3184	29	**3297**	36	2116	32
0.20%	2708	83	3155	57	**3261**	73	2084	64
0.30%	2668	123	3127	86	**3225**	108	2053	95
0.40%	2628	163	3099	114	**3190**	144	2022	125
0.50%	2589	202	3071	142	**3154**	179	1992	156
0.60%	2550	241	3043	169	**3120**	214	1962	185
0.70%	2512	279	3016	197	**3085**	248	1933	215
0.80%	2474	317	2989	224	**3051**	282	1904	244
Panel B: VAR								
0.00%	3721	0	**4362**	0	3276	0	3568	0
0.10%	3681	41	**4331**	30	3247	29	3533	36
0.20%	3640	81	**4301**	61	3218	59	3498	71
0.30%	3600	121	**4271**	91	3189	87	3463	106
0.40%	3561	160	**4241**	121	3160	116	3428	140
0.50%	3522	200	**4211**	150	3132	145	3394	174
0.60%	3483	238	**4182**	180	3104	173	3360	208
0.70%	3445	277	**4152**	209	3076	201	3326	242
0.80%	3407	315	**4123**	238	3048	228	3293	275
Panel C: Neural Networks								
0.00%	4139	0	5053	0	4338	0	**5613**	0
0.10%	4053	86	4933	120	4265	73	**5523**	89
0.20%	3969	170	4816	237	4193	145	**5436**	177
0.30%	3886	253	4701	352	4122	216	**5349**	263
0.40%	3805	334	4589	463	4053	286	**5264**	349
0.50%	3725	414	4480	573	3984	354	**5180**	433
0.60%	3648	491	4373	680	3916	422	**5097**	515
0.70%	3571	568	4269	784	3850	488	**5016**	597
0.80%	3497	642	4167	886	3785	554	**4936**	677
BUY AND HOLD	3230							

Notes: Numbers in bold indicate the best model within a forecasting technique. Shaded numbers indicate that the model and forecasting technique outperform the buy-and-hold investment.

Conclusion

The results of this study suggest that EREIT returns are positively related to stock, size, and book-to-market factors. Nevertheless, these relationships are quite volatile, with stocks and size being predominant until the early 1990s, while the book-to-market and size factors dominate thereafter. With bonds, a generally positive but weak relationship is found, whereas with real estate, the relationship exhibits much variability and seems to be cyclical. The explanatory power of the four models tested varies considerably through time.

Until the beginning of the 1990s, the R^2 was generally above 60%, it subsequently fell severely and since the beginning of the millennium it has been recovering but has not achieved the levels of the 1980s. The R^2 of the two models including the size and book-to-market factors did not suffer as strongly as that of the other two models.

A nonlinear linkage with the five factors is likely to be at play because the neural network predictions outperform the linear forecasting techniques. Judging with statistical criteria, the one-factor model of Sharpe (1964) generally yields the best linear forecasts. However, the trading strategy that achieves the highest profits is the one conceived with the neural network forecasts on the five-factor model. Overall, this paper highlights the importance of models including the Fama and French (1993) factors, as well as the superiority of neural networks as a forecasting tool. In particular, the hybrid nature of real estate securities can be exploited for prediction purposes. This is relevant for portfolio managers making investment decisions as profitable forecasts may be made, but most importantly, this finding presents an alternative to forecasters as they will not have to rely exclusively on economic and financial variables to make profitable predictions.

Future research could aim to better understand the nonlinear links between publicly traded real estate and stocks, bonds, real estate, size, and book-to-market ratios. The use of other explanatory variables, forecasting techniques, as well as data from other countries could also be of interest in order to provide further evidence on the usefulness of quantitative forecasts in devising portfolio strategies. Further efforts could also concentrate on the evaluation of forecasting techniques through trading strategies, focusing on other performance measures important to portfolio managers such as the Sortino ratio, maximum drawdown or expected shortfall. Finally, the strong results in favor of neural networks suggest that additional forecasting attempts should use this technique as the benchmark to beat.

Endnotes

1. NAREIT website: http://www.nareit.com/library/industry/marketcap.cfm.
2. For a review of the financial economics literature on the environment, performance, and diversification benefits of securitized real estate, see Corgel, McIntosh, and Ott (1995), Glascock and Ghosh (2000), Worzala and Sirmans (2003), and Zietz, Sirmans, and Friday (2003).
3. The guilt-equity yield ratio is defined as the ratio of the income yield on long-term government bonds to the dividend yield on stocks. Assuming that the guilt-equity yield ratio has a long-term equilibrium level, stocks are thought to be expensive (cheap) with respect to bonds if the ratio is higher (lower) than the long-term equilibrium level.
4. For a review on market efficiency, see Fama (1970).
5. The starting date and the frequency selected were dictated by the NCREIF data.
6. Previously known as the NAREIT EREIT series. It was renamed in March 2006.
7. Excluding the correlation between the smoothed and unsmoothed real estate series.
8. ARIMA specifications were also examined, but the correlograms and partial autocorrelograms did not reveal the existence of AR or MA components in the EREIT time series. Hence, trading strategies such as momentum are not envisaged in this paper.
9. A detailed explanation of the Levenberg-Marquardt optimization algorithm for training neural networks is found in Hagan and Menhaj (1994).
10. Out-of-sample forecasts are evaluated over 30% of the sample (35 observations).
11. Gerlow et al. (1993) point out that statistical criteria may not be relevant for determining the profitability of a forecast in a trading strategy.
12. Clayton and MacKinnon (2003) also suggest that there is a steady increase over time in the proportion of volatility not accounted for by stock, bond, and real estate factors.

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