Do the individual moments of REIT return distributions affect institutional ownership patterns?

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Abstract This paper examines the determinants of institutional investment demand for Real Estate Investment Trust (REIT) common stock. Specifically, it explores whether the demand function of institutional investors is dependent on the first four moments of the REIT returns distribution. The objective is to determine whether institutional investment decisions concerning REITs are influenced by individual stock attributes such as the mean return, standard deviation of returns, skewness of returns and kurtosis of returns. The results suggest that standard deviation plays a significant role in the institutional demand for REITs, but no significant role is found for the higher moments of the return distribution. The results also suggest institutional investment in REITs is predictable a priori using the moments of the REIT return distribution.

Keywords: *Real Estate Investment Trust, institutional ownership, mean, standard deviation, skewness, kurtosis*

Introduction

Real Estate Investment Trusts, or REITs (pronounced 'reets'), are companies that buy, develop, manage and sell real estate assets, providing an efficient and cost-effective way to invest in professionally managed portfolios of real estate assets. Since REIT securities qualify as pass-through entities, they must distribute the majority of their income to investors or face taxation at the corporate level. Real Estate Investment Trust shares are traded like common stocks on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and National Association of Securities Dealers (Nasdaq) exchange providing real estate investors with greatly enhanced liquidity over traditional real estate investments.

Various studies have examined the determinants of institutional demand for common stocks. Theoretically, institutional demand for common stocks should be a function of expected returns and the risk–return attributes of stocks. The measurement of returns is non-controversial, but risk measurement can be examined in several ways. The capital asset pricing model (CAPM) framework has been widely employed. Attempts have been made to use financial ratios to capture the risk factor. In a recent study, Eakins *et al.* (1998) found that institutions avoid stocks with extremely high or low betas, current ratios, debt ratios or return on assets measures. Various other studies have used the higher moments of the returns distribution for an individual stock as risk measures (standard deviation, skewness and kurtosis).

Under the assumptions of the CAPM, institutional investors should hold diversified portfolios. It is often argued that institutional managers should make investment decisions based upon an investment's marginal impact upon such a diversified portfolio. Investment decisions could instead be based upon the individual attributes of an investment rather than the investment's marginal portfolio impact. A number of studies of common stock investment behaviour have examined both the CAPM and alternative models of asset pricing behaviour. Some of these have been devoted to the investigation of the relationship between investor demand for stocks and the higher moments of the returns distribution.

The objectives of this study are twofold. First, it examines the determinants of institutional demand for REIT common stock, using the first four moments of the returns distribution computed in the conventional fashion. This study therefore seeks to determine whether REIT institutional investment decisions are based upon firm specific risk attributes. The second phase of the study examines whether it is possible to develop reliable a priori forecasts of the institutional demand for REIT common stocks.

Review of the literature

Cready (1994) examined the determinants of investor demand for common stock. He found that individual investors' demand for riskier, larger and low dividend yield stocks increased with wealth. He also found that relative to individuals, institutions prefer the stocks of larger firms, S&P500 firms, and firms paying lower dividend yields. In a study of the effect of wealth on individual portfolio asset allocation decisions, Cohn *et al.* (1975) found a pattern of decreasing relative risk aversion. In other words, their findings suggest that the proportion of a portfolio that is allocated to risky assets increases with the wealth of the individual holding the portfolio.

Investor behaviour with respect to higher moments of the distribution of returns has been examined in a number of studies. Examining the relationship between investment demand and an investor's perceptions of investment utility, Benishay (1987) developed a fourth-degree polynomial investor utility function. The function is further examined in a comment by Moses (1989) and Benishay's (1989) reply. Benishay (1992) further restricts the fourth-degree polynomial utility function to reflect decreasing absolute risk aversion consistent with Pratt (1964) and Arrow (1971). The implications are that the risk premium is positive and decreases as wealth increases.

Conventional theory suggests a positive preference for the first and third moments and an aversion to the second and fourth moments.

A study by Badrinath *et al.* (1989) examined institutional investment behaviour with regard to the prudent man hypothesis. The prudent man hypothesis suggests that the institutional manager should consider the total risk of each individual asset held. Under the Employee Retirement Income Security Act (ERISA) and common law, each investment must be prudent when considered in isolation, implying that the variance, skewness and possibly kurtosis of returns should be considered investors acting in a fiduciary capacity. Their results indicate that institutional ownership exhibits a positive relationship with firm size, a negative relationship with total risk and an indeterminate relationship with beta.

Eakins *et al.* (1997) find that institutions appear to seek high beta common stocks and tend to avoid stocks with high unsystematic risk. They conclude that the traditional CAPM positions regarding investor behaviour are not well supported. Their results also indicate that institutional investors evaluate common stocks based on the attributes of a stock's return distribution. Their findings indicate that institutions are highly averse to standard deviation and substantially averse to skewness and kurtosis in individual stock returns. They also conclude that there is some evidence of investor preference for stocks of larger firms as measured by market capitalisation. Their evidence also indicates that institutions strongly prefer firms listed on the NYSE and dislike those listed on the AMEX.

Studies by Arditti (1967) and Markowitz (1952) suggest that investors prefer positive skewness and dislike negative skewness. Kraus and Litzenberger (1976) also conclude that investors prefer positive skewness in returns. Kane's (1982) results also support this position. Stephens and Proffitt (1991) also find that skewness (in addition to mean and variance) in returns is a significant factor in explaining the performance rankings of international mutual funds. Their results indicate that kurtosis is not a significant factor for international fund investors.

A study by Turner and Weigel (1992) examines the daily returns distributions of the S&P 500 and Dow Jones Industrials indices. The results indicate that the 1980s had significantly higher levels of skewness and kurtosis in the return distribution than any other decade.

Results from a study by Scott and Horvath (1980) illustrate that, for an investor consistent in the direction of moment preferences, there is a positive (negative) preference for positive (negative) values of every odd central moment and a negative preference for every even central moment. The research further illustrates that investors who are not strictly consistent in preference direction must possess, on average, negative preference for even central moments and positive preference for odd central moments. They speculate that kurtosis is viewed as another aspect of variance and, since diversification reduces kurtosis much more rapidly than variance, it is not as important to investors.

In somewhat conflicting studies Singleton and Wingender (1986) find that skewness in returns for both portfolios and individual stocks does not persist over time while Muralidhar (1993) finds evidence that skewness in stock returns persists over time.

Aggarwal and Rao (1990) hypothesise that institutional ownership leads to more frequent information releases, fewer surprises and fewer errors. They find evidence of significant skewness and kurtosis in equity returns. The increased

Table 1 Descriptive statistics for the data. Average values for each independent variable across the full sample, by year

	1988	1989	1990	1991	1992	1993	1994	1995	1996
STD (%)	1.86	2.32	2.71	3.21	2.51	2.81	1.86	1.59	1.49
SKEW	0.1693	0.4017	0.1515	0.5756	0.2542	0.5452	0.2690	0.1701	0.2944
KURT	2.5915	6.1513	4.2177	5.7993	2.9409	3.2867	2.8091	2.9539	2.7187
MEAN (%)	0.07	0.00	−0.10	0.19	0.11	0.20	0.04	0.09	0.12
Market capitalisation[a]	$250.98	$247.15	$191.37	$192.90	$185.64	$283.36	$340.18	$398.78	$429.45
All Institutions	19.72	19.31	18.28	18.35	15.81	22.54	35.52	39.04	40.60
Banks (%)	5.49	4.83	3.74	3.51	2.77	3.32	5.01	3.79	3.81
Insurance Companies (%)	1.38	1.27	0.93	1.11	0.98	1.68	4.39	4.31	3.47
Investment Companies (%)	3.34	3.72	2.48	2.96	3.25	5.97	7.84	10.21	10.26
Investment Advisors (%)	8.20	7.87	9.72	9.44	7.87	10.90	16.76	18.31	21.03
Other Institutions (%)	1.31	1.60	1.42	1.33	0.95	0.67	1.53	2.43	2.03
n	46	51	50	47	58	69	122	148	164

[a] The total year-end market capitalisation of the sample REITs, in millions of dollars.

quality in informational flows leads to an inverse relationship between institutional ownership and variance, skewness and kurtosis in returns. A study by Damodaran (1985) concludes that return variance is jointly determined by the event structure and accuracy of the information structure, that skewness is jointly determined by the event structure and the bias in the information structure, and that kurtosis is jointly determined by the event structure and the frequency of information releases relative to the frequency of natural events. Campbell and Hentschel (1992) develop a model incorporating volatility feedback which partially explains the negative skewness and excess kurtosis of US stock returns for the period 1926–88.

The data

The sample includes all equity REITs listed on the NYSE, AMEX and Nasdaq daily returns files from the Center for Research in Security Prices (CRSP). The sample has been screened to eliminate REITs that do not have returns data throughout an entire sample year. Securities not described as 'ordinary common' by CRSP or having duplicate six-digit CUSIP numbers reported are eliminated to exclude non-voting shares. The final sample consists of daily returns on the stocks of over 150 firms for 1985–96. Summary statistics on the data are reported in Table 1.

The institutional ownership data were obtained from Control Data Advisors (CDA) Investment Technologies' Spectrum for the years 1988–96. These data consist of end of year institutional ownership filings required by the Securities and Exchange Commission (SEC). All institutions with investment control of over $100m must report quarterly to the SEC equity holdings above 10,000 shares and with market value above $200,000. The data set used in this study contains all filings made at the end of each year for 1988–96.

Methodology

This study examines whether certain measures of risk and return of common stocks influence institutional investment decisions. It seeks to determine whether the percentage of the institution's portfolio invested in a REIT common stock is affected by the measures of risk and return discussed below. The second phase of the study deals with the ability to forecast institutional investment using these measures.

In the first step, the analysis uses the daily returns data to calculate the mean return for each year for each of the

REIT common stocks in the sample. The variables used in this study consist of the mean return, the second, third and fourth moments of the returns distribution, the natural logarithm of market capitalisation, and dummy variables to categorise whether the stock is listed on the NYSE, the AMEX or Nasdaq (Nasdaq being the omitted class variable). The second moment (variance), third moment (skewness) and fourth moment (kurtosis) are employed as risk measures capturing the individual risk of a common stock.

Risk measures

The mean daily return is computed as follows:

$$MRET_i \frac{\sum_{t=1}^{n} R_{it}}{n} \qquad (1)$$

where R_{it} is the daily cum dividend return for firm i on day t as reported on the CRSP daily return tapes.

The CRSP daily returns data for the following moments of the returns distribution are used to calculate the standard deviation for each of the firms:

$$STD_i = \left(\frac{\sum_{i=1}^{N} (X_{it} - \overline{X}_i)^2}{n} \right)^{1/2} \qquad (2)$$

where $\overline{X}_i$ is the mean daily return for firm i for the year.

The skewness of daily returns is calculated as follows:

$$SKEW_i = \sum Z_i^3 \left[\frac{n}{(n-1)(n-2)} \right] \qquad (3)$$

where $Z_i = (X_i - \overline{X})/S)$, n is the number of observations, and S is the standard deviation of the returns series.

Finally, kurtosis is computed as

$$\begin{aligned} KURT_i = \sum Z_i^4 \times n(n+1) \\ /(n-1)(n-2)(n-3) \\ -3(n-1)^2 \\ /(n-2)(n-3) \end{aligned} \qquad (4)$$

where Z_i is defined as above.

The percentage of firm shares held by institutional investors for each firm (or the proportion of its total shares held by institutions) is calculated as follows:

$$IOWN_i = \frac{\text{shares held by institutions in firm } i}{\text{shares}_i} \qquad (5)$$

where $IOWN_i$ is the percentage of firm's shares held by institutions, and shares$_i$ is the number of shares outstanding in firm i stock.

The data set consists of those institutions reporting ownership interest to the SEC. Each institution has the alternative of investing in REITs in each year from 1988 to 1996. Separate regressions are estimated for each year.

Institutions are classified by type according to the designations provided by CDA Spectrum. This source categorises institutions as Banks, Insurance Companies, Investment Managers or Investment Advisors (including mutual funds). Institutions not reported in the directory are assigned to a category called 'Other'. Descriptive statistics for the data set are reported in Table 1.

The model

The following model is estimated as described below.

$$\begin{aligned} IOWN_i = a + b_1 MEAN_i + b_2 STD_i \\ + b_3 SKEW_i + b_4 KURT_i \\ + b_5 LNMKTVAL_i \\ + b_6 NYSE_i + b_7 AMEX_i + e \end{aligned}$$

where $IOWN_i$ is the percentage of firm shares held by institutions (equation 5), $MEAN_i$ is the mean daily returns for firm i (equation 1), STD_i is the standard deviation of daily returns for firm i (equation 2), $SKEW_i$ is the skewness of daily returns for firm i (equation 3), $KURT_i$ is the kurtosis of daily return for firm i (equation 4), $LNMKTVAL_i$ is the natural log of firm size in terms of end of year market value for firm i, $NYSE_i$ is a dummy variable to categorise by stock exchange listing equal to 1 if firm i is listed on the NYSE, 0 otherwise, and $AMEX_i$ is a dummy variable to categorise by stock exchange listing equal to 1 if firm i is listed on the AMEX, 0 otherwise. The Nasdaq stocks are the omitted category.

The neural network models

Neural networks (NN) are widely used in the evaluation of economic relationships. These techniques have been found useful in determining direct and 'hidden' dependencies between explanatory variables and the variable(s) to be explained. In these networks, processing elements (PEs) are combined into layers between input variables and the desired output. Layers that fall between input and output are classified as 'hidden' layers. In the case where the output layer is known, the network selected will seek to create the best possible connection weights between input and desired output, thereby maximising the explanatory power of the model.

Data sets are typically separated into 'learning' and 'testing' groups. This study examines consecutive years of data, using the most recent year to predict the following year in a 'feedforward network'. Information from the input layer passes through intermediate layers using transfer functions defined by the user that will achieve the objective function desired. This process separates neural computing from traditional artificial intelligence or linear models. Given the non-parametric form of the network process, NNs require no predetermined rules of behaviour. These are determined by the network selected and the objective function of reducing the error between actual outputs desired and the incoming connection weights. Therefore, as the network 'learns' from the input stimuli and the desired output, a non-linear multilayer network is produced that will combine the findings from all layers to produce the desired results. In this manner, NN often produce improved results and more robust models than those found in traditional models.

The models

An extensive literature has developed in the field of NN models applied to economic and financial problems. The structure of NN models varies widely. It is determined by the PEs, their interconnections and the model's activation function. A PE may have many input paths, resulting in an internal activity level for each element in the system. A completed network includes many PEs joined together by layers. The typical system has a combination of three layers: input, hidden and output. More hidden layers are possible in more complex models. The PEs in these layers may be fully or partially interconnected.

The input layer of PEs includes what are traditionally identified as explanatory (or independent) variables. Given a series of matching output variables (dependent variables), the network 'learns' the relationship between the two layers by developing a 'hidden' layer that generates the least-error weights for the explanatory variables. In this manner, the

NN appears to be a method for generating a complex formula for the hidden layer(s) that defines the best-fit relationship between input and output layers. Neuron weights define the optimal curvilinear relationship of independent and dependent variables.

The process of mapping the best-fit relationship between input and output is known as learning, training or adaptation. By examining *ex post* data, the proper method of learning will create a model which improves upon traditional statistical techniques (eg regression models) by generating relatively stable coefficients even when the data are not well behaved (noisy). Unlike typical regression models, the learning phase in NNs repeatedly defines the relationship weights such that the desired output is achieved. Under certain circumstances, however (eg when weights must be 0 or 1), the networks coefficients become equivalent to linear regression coefficients. When continuous values are allowed, NNs should produce less error than other forms of pattern recognition. Even in cases where input data are noisy or incomplete, NNs seem to produce more reasonable results.

The NN model uses the identical data and variables to the ordinary least squares (OLS) methodology, although variables in NN models do go through multiple transformations. The output variable is the percentage of institutional ownership, as described earlier in the data section. Each PE is connected to each of the input PEs and to the output PE. There is also a bias term included in each model. The bias term is similar to the intercept term in a regression model.

Throughout the estimation process, the model generates weights (which describe the strength of the connections) for the input layer PEs. A signal is sent from each input PE to each of the PEs in the hidden layer where the weights are summed. The result is a linear combination of the product of the weights and the input variables. This estimated value is then transformed through a transfer function and transmitted as a signal to the output PE. A final weight is applied to determine the contribution to the estimated output variable value. As Gorr *et al.* (1994), notes, each of these middle layer PEs has the capability of separately modelling the relationship between the input and output variables. The TanH function is capable of switching these models on and off.

The potential advantages of NN models are extensively discussed in Hill *et al.* (1994). The NN models can apparently extract a more complex set of information from the functional form embedded in the data. The Hill *et al.* (1994) paper further states that NN models are inherently non-linear and are capable of partitioning the sample space and building different functions in different portions of that space. In comparing NN models and regression models, Hill *et al.* (1994) concluded that the NN models have an ability to perform well when the functional form is unknown, which gives them an inherent advantage. Their paper also cites a number of studies which generally find that NN models perform better than logistic regression models and discriminate analysis models. There are difficulties inherent in NN models. As noted, it is impossible to calculate anything analogous to regression coefficients, there is always the chance of overfitting, and the estimation time is usually quite high.

Identifying the learning and testing data sets

Use was made of learning and testing data sets that have one output: *IOWN*.

The learning files are for years 1988–96, with testing files from 1989 to 1996. In each case, raw data were used to best the model's ability to predict the next year's institutional ownership using the current year data for learning.

The model building and testing process may be summarised as follows. The model was estimated on 1988 data and tested on data from 1989, estimated on 1989 data and tested on 1990 data, etc to 1996.

The evaluation of the forecasts from an NN model is particularly difficult. There is no way to determine the contribution of a particular input variable. Nothing analogous to regression coefficients or *t* statistics can be calculated. The accuracy of the forecast itself (ie forecast versus actual values) is evaluated using the mean correlation coefficient between the actual and forecast values.

Regression results

The data

Descriptive statistics for the REIT data are presented in Table 1, and several interesting trends are apparent. First, the percentage of REIT stock owned by all institutions increased from 19.72 per cent in 1988 to 40.60 per cent in 1996, indicating a significant rise in demand for REITs over the period. In addition, the Investment Advisors group maintained the highest percentage ownership over the entire sample period, ending with 21.03 per cent ownership in 1996. Finally, Table 1 indicates that most of the increase in REIT institutional ownership over the period can be attributed to Investment Companies and Investment Advisors.

In addition to changes in ownership levels, certain other trends have emerged over the period studied. The standard deviation of returns is found to be highly variable over the study period, with the highest levels occurring from 1989 to 1993 and the peak occurring in 1991. By 1996, the standard deviation had fallen to the lowest level of the sample period. The skewness of returns is positive in all years of the study, peaking in 1993 at 0.58 and reaching a minimum of 0.298 in 1996. The kurtosis of returns is highest from 1989 to 1991, with the maximum of 6.158 occurring in 1989. A gradual decline in kurtosis has been observed since then, with the 1996 level being only 2.72. Mean daily returns are positive in eight of the nine sample period years, with a high of 0.2 per cent occurring in 1993, and a low of −0.1 per cent occurring in 1990.

With these data, a regression analysis of ownership demand for institutions in the aggregate and for the five separate industry group categories as defined by CDS Spectrum was performed. The regression coefficients and adjusted R^2 values are presented in Table 2.

Results across the entire study period

The regression results appear in Table 2. The 'All Institutions' results in Panel 1 indicate that the model has good explanatory power, with adjusted R^2 values ranging from 0.33 to 0.52. The variables demonstrating the most consistency in terms of significance are *LNMKTVAL* and *STD*.

The coefficient for the standard deviation variable (*STD*) is significant in five of the nine years. It is interesting to note that the first three significant coefficients occur in 1988–90, with all three coefficients being negative. In 1991 and 1992, the coefficients remain negative but decline in magnitude and lose their significance. The two remaining significant coefficients occur in 1993 and 1995 and are positive in both

Table 2 Linear regression results for individual moments model by institution type

Panel 1

All Institutions	1988	1989	1990	1991	1992	1993	1994	1995	1996
INTERCEPT	0.5152***	0.2685***	0.3379***	0.3037***	0.2962***	0.3936***	0.5453***	0.5942***	0.6636***
STD	−8.8517***	−4.4318***	−2.5088**	−1.4190	−0.2230	4.8138	−0.8735	5.7674*	−2.2292
SKEW	0.0053	−0.0208	0.0203	0.0217	0.0388	−0.1310**	0.0031	0.0161	−0.0079
KURT	0.0047	0.0033	−0.0075*	−0.0076	−0.0011	0.0177*	0.0013	−0.0003	−0.0053
MEAN	−40.3108	82.7873***	0.3990	11.9545	−10.9145	−44.0048**	34.0330	−33.9577	42.3688
LNMKTVAL	0.0144	0.0028	0.0421**	0.0552**	0.0603***	0.0853***	0.1134***	0.1264***	0.1087***
NYSE	−0.1021	0.0812	0.0802	0.0721	0.0567	0.0065	0.0427	−0.0568	−0.0841
AMEX	−0.1839**	−0.0418	0.0166	0.0833	−0.0056	−0.0271	−0.0554	−0.1200	−0.1675**
Adj. R^2	0.3292	0.5178	0.4118	0.3281	0.3561	0.4583	0.4321	0.3548	0.3685
n	45	48	48	44	58	69	122	148	164

Panel 2

Banks	1988	1989	1990	1991	1992	1993	1994	1995	1996
INTERCEPT	0.1637***	0.0995***	0.0723***	0.0517**	0.0421*	0.0616***	0.0910***	0.0504***	0.0621***
STD	−2.9586***	−1.3001***	−0.3528	0.3331	0.3096	1.1258**	0.2246	0.8102*	−0.0198
SKEW	0.0099	0.0088	−0.0018	0.0074	0.0012	−0.0252**	−0.0073	0.0056	−0.0041
KURT	0.0006	−0.0006	−0.0027**	−0.0020	−0.0005	0.0023	0.0010	−0.0002	0.0006
MEAN	−10.3731	8.3034	−11.4601**	−6.3369	−3.1699	−9.8844**	1.8216	−12.0808***	−1.6334
LNMKTVAL	−0.0006	0.0003	0.0098	0.0050	0.0075	0.0127**	0.0190***	0.0103***	0.0121***
NYSE	−0.0605***	−0.0185	0.0023	0.0064	0.0084	−0.0082	−0.0120	0.0037	−0.0010
AMEX	−0.0688***	−0.0345**	−0.0111	−0.0051	−0.0074	−0.0014	−0.0176	−0.0068	−0.0136
Adj. R^2	0.2722	0.3466	0.1558	−0.0050	0.1278	0.2404	0.2358	0.1913	0.2957
n	45	48	48	44	58	69	122	148	164

Panel 3

Insurance Companies	1988	1989	1990	1991	1992	1993	1994	1995	1996
INTERCEPT	0.0125	0.0075	0.0122	0.0161	0.0195	0.0125	0.0240	0.0287*	0.0587***
STD	−0.3517	−0.3401	−0.1906	−0.0401	−0.1251	0.2292	0.1439	1.5436**	0.1938
SKEW	0.0000	−0.0048	−0.0019	0.0093	0.0115	0.0015	−0.0071	0.0043	0.0057
KURT	0.0004	0.0002	−0.0010	−0.0019	−0.0005	−0.0004	0.0002	0.0002	−0.0020
MEAN	6.5437	1.6129	0.3532	−0.8653	−2.5307	−2.6154	5.2681	−17.0786***	0.7705
LNMKTVAL	0.0014	−0.0027	0.0008	0.0034	0.0048	0.0018	0.0105*	0.0138**	0.0046
NYSE	0.0157	0.0202	0.0158	0.0121	0.0115	0.0170	0.0477**	0.0311**	−0.0151
AMEX	−0.0068	−0.0050	0.0023	0.0087	0.0031	−0.0051	0.0167	0.0187	−0.0321*
Adj. R^2	−0.0954	−0.0766	−0.1086	−0.1168	−0.0542	0.0036	0.1614	0.1491	0.0289
n	45	48	48	44	58	69	122	148	164

Panel 4

Investment Companies	1988	1991	1992	1993	1994	1995	1996
INTERCEPT	0.0952***	0.0574**	0.0727***	0.1169***	0.1208***	0.1756***	0.1785***
STD	−1.1329**	−0.6216*	−0.4119	1.2696	−0.3311	1.4039	−0.1399
SKEW	0.0034	−0.0066	0.0099	−0.0310	−0.0040	0.0099	−0.0164
KURT	−0.0003	−0.0003	0.0009	0.0059*	0.0007	0.0010	−0.0011
MEAN	−9.8043***	9.7891**	0.8432	−11.5714	14.2401	24.1655**	21.0941**
LNMKTVAL	0.0094	0.0172**	0.0205***	0.0298***	0.0295***	0.0446***	0.0405***
NYSE	−0.0164	0.0224	0.0216	−0.0038	0.0189	−0.0512*	−0.0347
AMEX	−0.0246	0.0290	0.0141	−0.0041	−0.0059	−0.0668**	−0.0212
Adj. R^2	0.2317	0.3266	0.3114	0.3364	0.3367	0.3293	0.2509
n	45	44	58	69	122	148	164

Table 2 continued

Panel 5							
Financial Advisors	**1988**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**
INTERCEPT	0.2183***	0.1615**	0.1483**	0.1972**	0.2958**	0.3226***	0.3406***
STD	−4.2142**	−1.2031	−0.1284	2.1116*	−0.9694	1.3573	−2.0838*
SKEW	−0.0045	0.0024	0.0176	−0.0728**	0.0214	−0.0019	0.0056
KURT	0.0009	−0.0025	−0.0003	0.0091*	−0.0008	−0.0006	−0.0020
MEAN	−21.8524***	12.9274	−2.6861	−18.9480	13.1117	−18.9754	21.6117
LNMKTVAL	0.0001	0.0262*	0.0254**	0.0391***	0.0499***	0.0508***	0.0462***
NYSE	−0.0336*	0.0267	0.0111	−0.0057	−0.0237	−0.0638	−0.0447
AMEX	−0.0842*	0.0325	−0.0210	−0.0195	−0.0514	−0.0779	−0.0986**
Adj. R^2	0.1796	0.2970	0.2207	0.3650	0.3094	0.2281	0.2778
n	45	44	58	69	122	148	164

Panel 6							
Other Institutions	**1988**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**
INTERCEPT	0.0256**	0.0171	0.0136	0.0054	0.0137	0.0168	0.0238*
STD	−0.1943	0.1127	0.1328	0.0776	0.0584	0.6523	−0.1795
SKEW	−0.0034	0.0092	−0.0015	−0.0035	0.0002	−0.0017	0.0013
KURT	0.0031***	−0.0010	−0.0006	0.0008	0.0001	−0.0007	−0.0007
MEAN	−4.8247	−3.5599	−3.3710	−0.9855	−0.4086	−9.9885*	0.5259
LNMKTVAL	0.0041	0.0033	0.0022	0.0020	0.0045	0.0068*	0.0052*
NYSE	−0.0075	0.0044	0.0041	0.0072	0.0118	0.0233*	0.0115
AMEX	0.0005	0.0182	0.0055	0.0030	0.0027	0.0128	−0.0020
Adj. R^2	0.4964	−0.1019	−0.0732	0.1092	0.1182	0.0905	0.0810
n	45	44	58	69	122	148	164

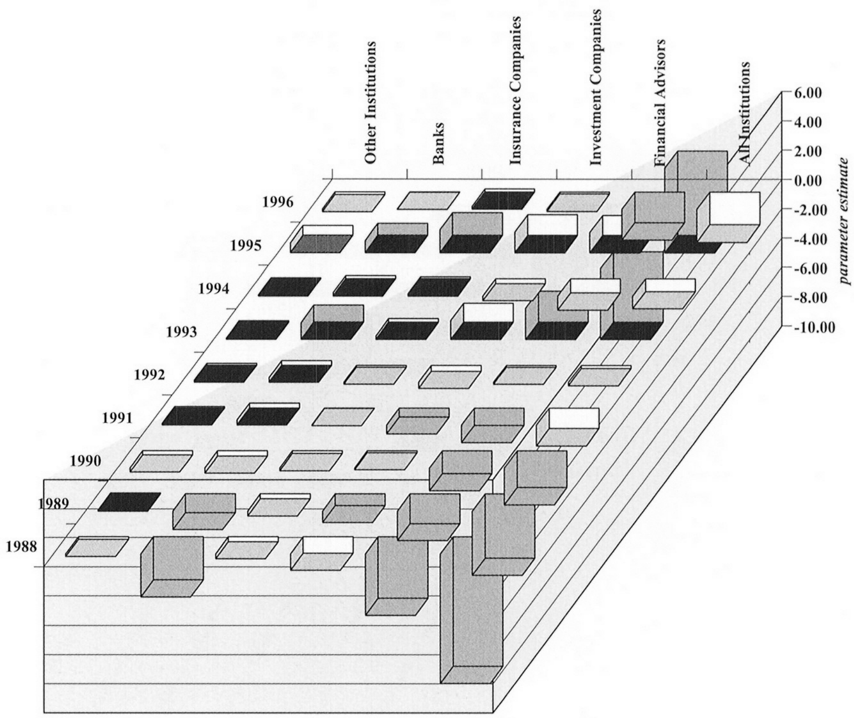
Note: ***coefficient significant at the 1 per cent level; **coefficient significant at the 5 per cent level; *coefficient significant at the 10 per cent level.

cases. This shift from significant negative to significant positive coefficients implies a general shift from institutional aversion to total risk in the early years of the study period toward an institutional preference for total risk later on. This shift is particularly apparent in Figure 1(a), where the coefficients and their associate levels of significance are displayed graphically. It is clear from this figure that the shift was driven primarily by Banks, Insurance Companies and Financial Advisors.

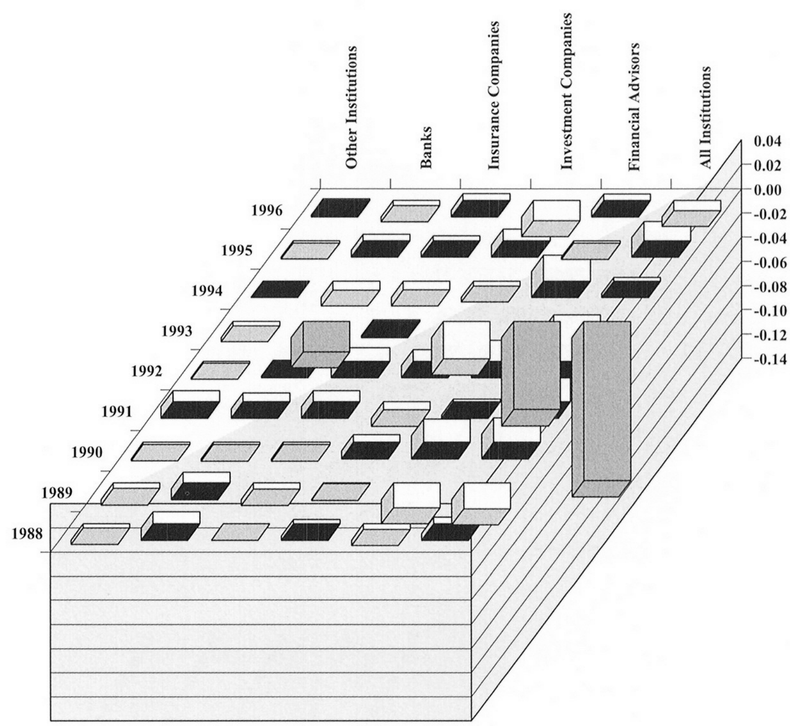
The coefficient for the skewness variable (*SKEW*) is significant in only one of the nine years, while the variable for kurtosis (*KURT*) is significant in only two of the nine years. The signs for the coefficients of both variables are inconsistent throughout. It is therefore concluded the third and fourth moments of the return distribution have little or no influence on REIT institutional demand. The inconsistent nature of these variables is very apparent in Figures 1(b) and (c).

Surprisingly, the mean return for a REIT appears to have little impact on its institutional demand. For the 'All Institutions' sample, the coefficients for *MEAN* are actually negative in four of nine years, and the signs are inconsistent between the only two significant results. Figure 1(d) shows no clear pattern for *MEAN* among any of the institutional investor groups.

The size variable (*LNMKTVAL*) exhibits positive coefficients throughout and they are significant for the final seven years, implying a considerable

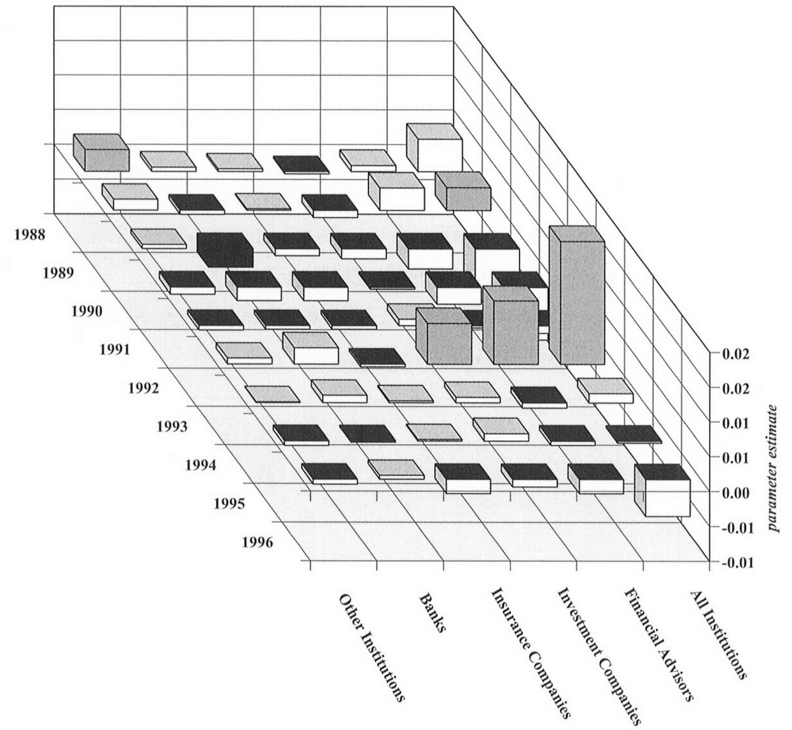


(a)

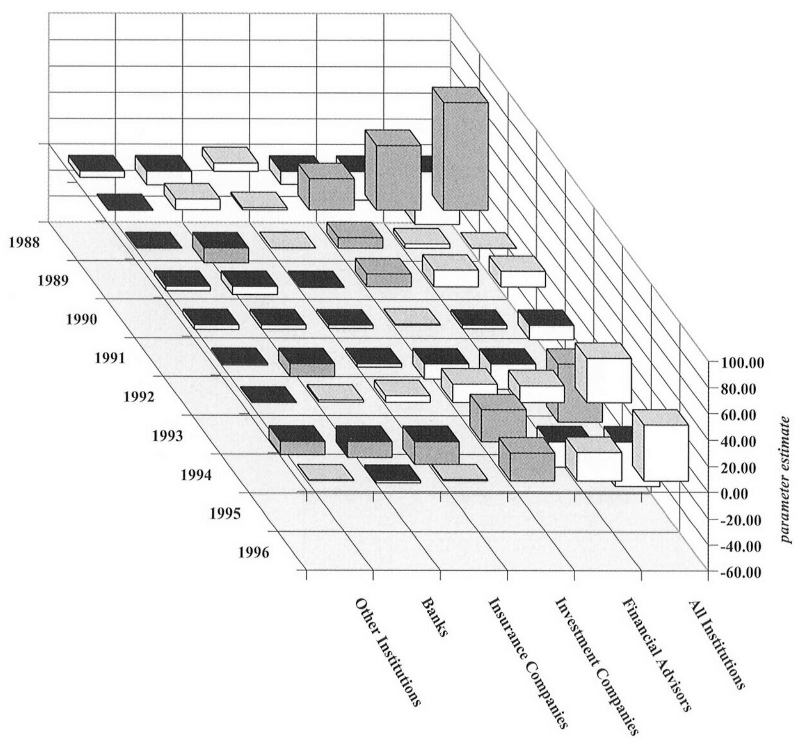


(b)

Figure 1 Linear regression parameter estimates (columns denoted by diagonals represent significance at the 10 per cent level): (a) estimates for *STD*; (b) estimates for *SKEW*; (c) estimates for *KURT*; (d) estimates for *MEAN*; (e) estimates for *LNMKTVAL*; (f) estimates for NYSE; (g) estimates for AMEX

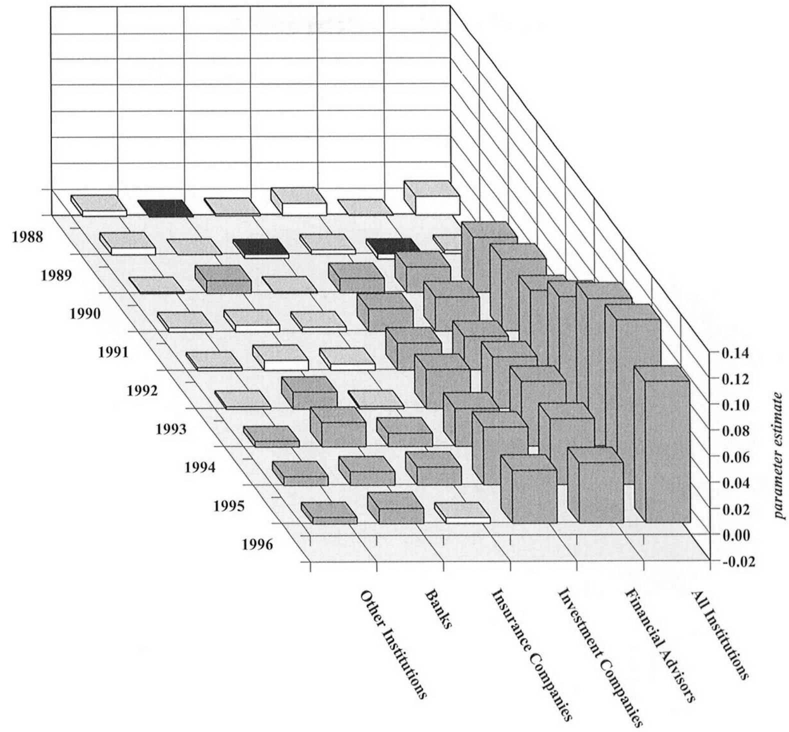


(c)

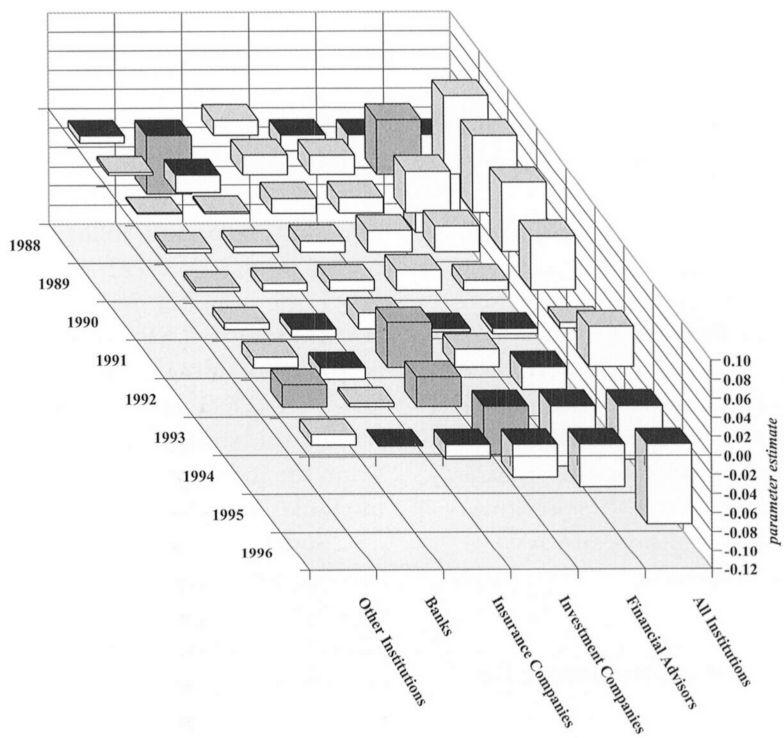


(d)

Figure 1 Continued



(e)



(f)

Figure 1 Continued

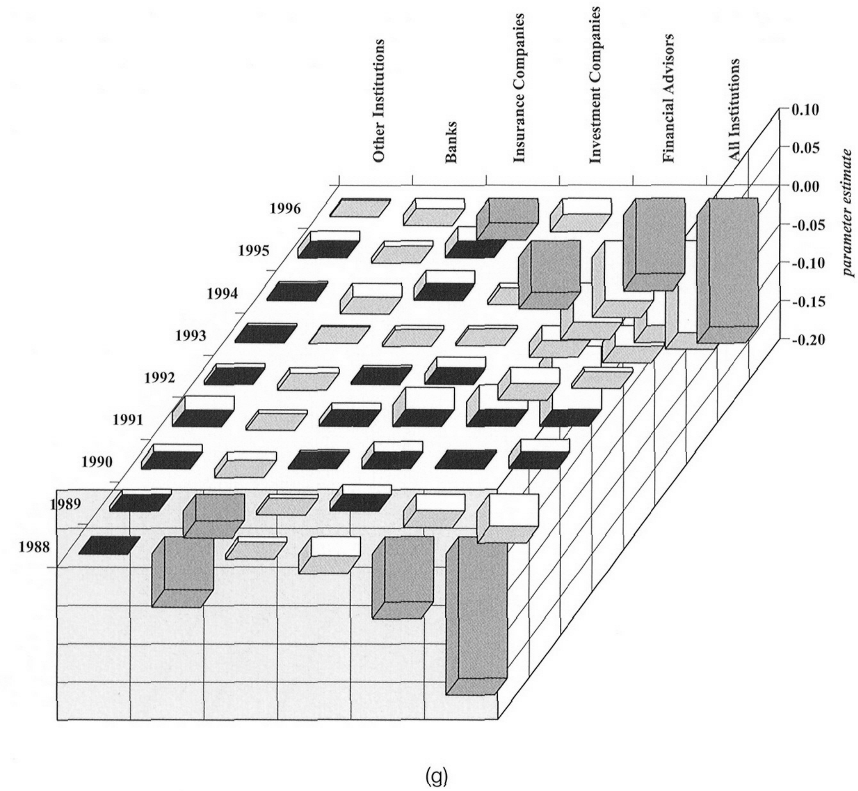


Figure 1 Continued

preference for size (liquidity). The institutional ownership groups exhibiting the strongest size preference are Investment Companies, Financial Advisors, and Banks, as is apparent in Figure 1(e). In addition, the increasing magnitude of the coefficients suggests that institutional demand for liquidity grew steadily over the study period.

The exchange dummy variables *NYSE* and *AMEX* are inconclusive. It is clear in Figures 1(f) and (g) that the signs are relatively consistent across institutional groups and time, but there are few significant coefficients.

Results of tests of a combined data sample

In order to gain further insight into the variables influencing institutional investment decisions, a combined sample was formed composed of REITs over the final three years of the study period and re-estimated the model. This single 1994–96 period was chosen because it represents a period following the REIT boom period of 1992–93, hence providing a better representation of the contemporary REIT market. This period also encompasses the highest levels of REIT institutional ownership within the study period. The results from the combined period are presented in Table 3.

Consistent with the previous findings, the size proxy (*LNMKTVAL*) is significant across all institutional types. Clearly, liquidity is a primary consideration for all types of institutional investors in terms of REIT selection.

In contrast, the coefficient for total risk (*STD*) is insignificant for the All Institutions category but examination of

Table 3 Combined OLS regression results by institution type for the most recent three years (1994–96)

Regressions n=434	All Institutions	Banks	Insurance Companies	Investment Companies	Investment Advisors	Other
INTERCEPT	0.6035***	0.0656***	0.0383***	0.1623***	0.3197***	0.0177**
STD	−0.0217	0.4071**	0.5622*	0.3050	−1.2894*	−0.0065
SKEW	−0.0035	0.0019	−0.0016	−0.0061	0.0029	−0.0006
KURT	−0.0002	0.0000	−0.0001	−0.0002	0.0003	−0.0001
MEAN	21.9476*	−6.7609***	−5.1658*	21.5804***	13.4672*	−1.1731
LNMKTVAL	0.1124***	0.0132***	0.0094***	0.0390***	0.0461***	0.0047**
NYSE	−0.0342	−0.0019	0.0192**	−0.0252*	−0.0426*	0.0163***
AMEX	−0.1260***	−0.0123*	−0.0014	−0.0301*	−0.0845***	0.0022
Adj. R^2	0.3882	0.2350	0.0970	0.2952	0.2844	0.1009

the regressions by institutional type reveals some divergence in individual risk preferences. Banks and Insurance Companies exhibit a significant preference for total risk, while Investment Advisors exhibit a significant aversion.

As expected, the skewness (*SKEW*) and kurtosis (*KURT*) coefficients are not significant in the regressions run on any of the institutional groupings.

The mean daily return variable (*MEAN*) is positive and significant for the All Institutions combined sample, but the results by institutional type reveal some divergence. Investment Advisors and Investment Companies exhibit positive preference for high returns, but Banks and Insurance Companies exhibit a seemingly irrational aversion to them. Coupled with Banks and Insurance Companies' previously discussed preference for total risk, the aversion to high returns is even more puzzling. One potential explanation, however, is that the results reflect an unsuccessful attempt to capture higher returns by targeting riskier REIT securities.

The exchange-listing variables indicate that Insurance Companies and institutions categorised as Other prefer NYSE-listed REITs, while Investment Companies and Investment Advisors tend to avoid them, as well as avoiding those listed on the AMEX. In fact, the All Institutions category demonstrates a significant negative preference for AMEX listed REITs and the signs corresponding to the regressions for the individual institutions are negative for all institutional types except Other, suggesting a general aversion to AMEX listed REITs.

Results of predictive power tests using ordinary least squares and neural networks

The primary advantage of OLS is that it is easy to perform and the results include coefficients which provide some measure of the impact of each independent variable. The disadvantage is that OLS models require a number of rather restrictive assumptions about the data. As noted in the preceding sections, NN models make no data assumptions and thus are potentially more reliable in a wide range of applications. It is difficult, however, to determine the impact of any variable in an NN analysis, and NN analyses can be very time consuming to perform.

Results of predictive power tests

By means of the combined All Institutions data, the regression model was estimated on each individual year's data and then the correlation coefficients

Table 4 Predictive power tests using linear regression

Year	No. of REITs	In-sample correlation coefficients	Out-of-sample correlation coefficient[a]
1996	164	0.6290	0.5538
1995	148	0.6209	0.5823
1994	122	0.6819	0.4547
1993	69	0.7170	0.6215
1992	58	0.6597	0.5585
1991	44	0.6614	0.6023
1990	48	0.7067	0.5258
1989	48	0.7679	0.4531
1988	45	0.6602	N/A

IOWN = *f* (*MEAN, STD, SKEW, KURT,* LNMKTVAL, NYDUM, AMDUM)
[a] In-sample correlations are calculated as actual versus predicted within a given year. Out-of-sample correlations are calculated using estimates from the model run on the previous year's data. For example, a model estimated using 1988 data is tested on the actual ownership levels for 1989.

Table 5 Predictive power tests for the user-controlled neural network

Year	No. of REITs	In-sample correlation coefficients	Out-of-sample correlation coefficient[a]
1996	164	0.5690	0.2290
1995	148	0.7690	0.1990
1994	122	0.7050	0.1390
1993	69	0.8730	0.3310
1992	58	0.9490	0.1140
1991	44	0.9990	0.5820
1990	48	0.9990	0.5140
1989	48	0.9990	0.1920
1988	45	0.9990	N/A

IOWN = *f* (*MEAN, STD, SKEW, KURT, LNMKTVAL*, NYDUM, AMDUM).

of the predicted versus actual institutional ownership levels were calculated on both the same year's (in-sample) data and on the subsequent year's (out-of-sample) data. The results of these tests appear in Table 4.

The next phase of the comparison involved performing identical tests of the predictive abilities of both the user-controlled and the automated NN models. These results appear in Tables 5 and 6 respectively.

The combined results of Tables 4–6 indicate that the out-of-sample results for the automated NN model are consistently better than those achieved with the user-controlled model, but that both NN models are generally inferior to traditional OLS regressions in terms of out-of-sample prediction.

Conclusions

This study investigated the institutional ownership demand for the first four moments of the return distribution of equity REITs. This was accomplished through a series of OLS regressions that include the four moments of the distributions and additional factors that are deemed likely to influence institutional REIT demand. In addition, it was investigated whether institutional ownership of REITs can be accurately forecast one year in the future using either traditional OLS regression techniques or less-traditional NN applications. The results obtained provide insight into the investment preferences of institutional REIT investors.

The regression results clearly indicate that size is the single most important

Table 6 Predictive power tests for the automated neural network

Year	No. of REITs	In-sample correlation coefficients	Out-of-sample correlation coefficient[a]
1996	164	0.4238	0.2494
1995	148	0.6360	0.3258
1994	122	0.4389	0.3757
1993	69	0.4356	0.3759
1992	58	0.4240	0.1492
1991	44	0.8091	0.6637
1990	48	0.8044	0.7483
1989	48	0.8659	0.4551
1988	45	0.9079	N/A

IOWN = *f* (*MEAN, STD, SKEW, KURT, LNMKTVAL, NYDUM, AMDUM*)
[a]In-sample correlations are calculated as actual versus predicted within a given year. Out-of-sample correlations are calculated using estimates from the model run on the previous year's data. For example, a model estimated using 1988 data is tested on the actual ownership levels for 1989.

factor influencing the institutional ownership of REITs. Across virtually all institutional types and time periods, the results indicate that larger REITs, on average, exhibit higher institutional demand. Therefore, it seems clear that REITs seeking institutional ownership should concentrate first and foremost on total market capitalisation.

The regression results also reveal an apparent shift from institutional aversion to total risk (standard deviation) in the early years of the study period toward a preference for total risk in the later years. Regressions run on combined data from the final three years of the study period suggest that Banks and Insurance Companies are the major factors behind the shift in preference.

Perhaps the most perplexing results were obtained from the combined 1994–96 sample, where Banks and Insurance Companies were found to exhibit a preference for high-risk REITs while exhibiting a simultaneous aversion to REIT returns. A possible explanation for these seemingly irrational results is that these institutions sought out higher-risk REITs in hopes of earning higher returns, but in fact ended up with portfolios of underperforming REITs instead.

These findings reveal that although size is the single dominant factor across all institutions, unique preferences exist for each of the institutional ownership types studied. In turn, this suggests that individual REITs could either be tailored to suit a particular institutional clientele or to appeal to the broadest cross section of institutions possible. One caveat, however, is that it was found that some institutional preferences shift over time, meaning any adjustments in REIT characteristics would need to take changing preferences into account.

The second focus of this study was to investigate whether REIT institutional ownership levels can be successfully forecast one year out. Tests involved estimating each model on the All Institutions category for a given year, and then using those estimates to predict the subsequent year's institutional ownership level. The correlation coefficients between the actual and predicted values were calculated using both OLS and NN approaches in order to assess the relative predictive abilities of each approach.

The findings suggest institutional ownership can be forecasted one year out with a reasonable degree of accuracy. In fact, many of the actual-versus-predicted correlation coefficients in the

Table 7 Transformations of variables included in the automated NN model

Year	*MEAN*	*STD*	*SKEW*	*KURT*	*NYDUM*	*AMDUM*	*LNMKTVAL*	*IOWN*
1996	Linear	Linear InvRt2	Linear Tanh	NIM Linear Fzrgt	NIM	Logical	Tanh	Log
1995	Linear Inv Tanh	Linear	Pwr2	Linear Tanh Fzrgt	Logical	Logical	Linear Tanh	Pwr2
1994	Pwr2 Fzrgt	Linear InvPwr2	Pwr2 Tanh	Linear Tanh	Logical	NIM	Linear Tanh	Log
1993	ExpExp Pwr4	Linear	Linear Pwr4	InvPwr4	Logical	Logical	Linear	Log
1992	Inv	Linear Exp Tanh	Linear Tanh	Linear InvPwr4 Tanh	Logical	Logical	Pwr2 Tanh	Inv
1991	Linear Pwr4 Tanh	Linear ExpExp	NIM	Linear Tanh	Logical	Logical	Pwr2	Rt2
1990	Linear Tanh	Linear Exp Tanh	Linear Pwr2 Tanh	NIM	Logical	Logical	Linear Exp	Rt2
1989	Linear	InvPwr4 Tanh	Linear Inv	NIM	NIM	Logical	Linear Pwr2	Rt2
1988	Tanh	Linear InvPwr2 ExpExp	Tanh	Linear ExpExp	Logical	Logical	Pwr2 Tanh	Pwr2

NIM: Not included in model; Linear: Identity function; Log: Natural logarithm function; LogLog: Log of Log; Exp: Exponential function; ExpExp: Exp of Exp; Pwr2: Square function; Pwr4: Fourth power function; Rt2: square root function; Rt4: fourth root function; Inv: inverse function (1/*x*); InvPwr4: 1.0/(fourth power function); InvPwr2: 1.0/(square function); InvRt2: 1.0/(square root function); InvRt4: 1.0/(fourth root function); Tanh: hyperbolic tangent function; ln *x*/(1–*x*): Log [*x*/(1–*x*)]; fzlft: fuzzy left; fzrgt: fuzzy right; fzraw: fuzzy centre on raw data.

later (high observation) years exceed 0.60, particularly when using the OLS approach. These findings provide further support for the feasibility of REITs tailoring their characteristics to meet the preferences of institutional investors.

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