# Analyzing the Nature of Institutional Demand for Common Stocks

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*This study uses Tobit regression and two different neural network models to investigate institutional investment behavior as evidenced in the relationship between the percent of institutional ownership of common stock and various firm-specific attributes (primarily financial ratios). We find support for the hypothesis that institutional investors rely upon a broad range of financial information beyond that found in the capital asset pricing model. The nonlinear relationships documented in this study differ from the conclusions reported in other recent papers. Generally, the neural network models yield the best forecasts of institutional ownership.*

## INTRODUCTION

The proportion of common stock shares controlled by institutional investors has increased dramatically in recent years, surpassing the 50 percent level of aggregate ownership for the first time in 1992. This trend illustrates the large and growing importance of institutional investors in the U.S. stock market. Although these investors potentially can exert great influence on the market, relatively few studies have examined the determinants of institutional demand for common stock. Little is known about which firm attributes attract or repel institutional investors.

The traditional belief is that the capital asset pricing model (CAPM) explains the risk return relationship. If all stocks are substitutable, there should be no relationship between the level of institutional demand for a stock and the stock's firm-specific factors. Investment managers relying on the CAPM could select firms by duplicating some stock index or by using some selection criterion peculiar to the institution. Because there is no reason to think these methods should result in any systematic selection procedure, a


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firm's financial ratios should not affect the level of institutional ownership of that firm's stock.

In this study a set of financial ratios commonly employed by financial analysts in investment decisions is selected. These ratios presumably capture financial characteristics of those firms in which institutions invest. In the first phase of the analysis we regress the percent of institutional ownership on this set of ratios for each of the years 1988 to 1991. Tests for linearity reveal that firm financial characteristics such as beta, firm size, and trading liquidity are nonlinear in their relationship to institutional ownership. Specifically, institutional investors tend to avoid the extremes in these financial ratios. This suggests the need for a nonlinear model. In order to investigate the possibility of nonlinearities, we construct and test various neural network (NN) models of the investment process.

Some studies have found that firm-specific factors influence investment demand. Dowen and Bauman (1986) find that the inclusion of institutional ownership, price earnings ratio, and market capitalization variables in a model with beta improves portfolio performance results. Badrinath, Gay, and Kale (1989) find that a number of factors other than beta influence the level of institutional ownership. O'Brien and Bhushan (1991) find a relationship between institutional ownership and the number of analysts following the stock. Hessel and Norman (1992) report that the debt ratio, the R&D to sales ratio, the net operating income to assets ratio, and firm size predict the percentage of institutional ownership. Del Guercio (1996) examines the role of the (Standard & Poor's) S&P ranking, liquidity, firm size, share volume turnover, market capitalization of equity, and whether the stock is traded on the NYSE on institutional ownership. Falkenstein (1996) examines mutual fund investment behavior and finds that funds have a preference for stocks with high visibility and low transactions costs and are averse to stocks with low idiosyncratic volatility. Falkenstein concludes that individual firm attributes are significant institutional decision parameters which supports the use of such attributes in this study.

Shefrin and Statman (1995) investigate the relationship between stock returns, beta, firm size, and the book to market value ratio. They find that investors prefer large companies with low book to market ratios. Fama and French (1995) examine the behavior of stock prices relative to size and book to market value. They find that high ratios values signal poor earnings and revenue growth. The stream of research by Fama and French (1981, 1988, 1992, 1993, 1995) appears to indicate that financial ratios affect investment decisions.

A natural question to emerge from these studies is why these variables are important to investors in an efficient market. One possible explanation follows from the literature cited above. Institutional fund managers may need to demonstrate the prudence of given investment decisions to reduce the possibility of client criticism (Badrinath, Gay, and Kale, 1989). Del Guercio (1996) points out that laws and regulations impact institutional investment behavior and often have unintended consequences. Prudent man behavior as accepted by the courts is based upon the characteristics of individual assets, not upon the asset's marginal effect on a portfolio.

Institutional investors may be concerned that their investments appear speculative, and this may influence their stock selection process. Such concerns could lead institutional investors to select firms that are relatively large, highly liquid, and stable. Badrinath, Gay, and Kale (1989) find that the fiduciary responsibility of institutional fund managers and the need to demonstrate the prudence of their investment practices affect institutional common stock investment decisions. Their findings indicate that institutional ownership is positively related to firm size, beta, trading liquidity, and the number of years the stock has been listed. They conclude that institutional investors want to be perceived as prudent investors. Del Guercio (1996) finds evidence that a substantial group of investors choose stocks because they are considered glamour stocks rather than on the basis of risk/return characteristics.

This study investigates whether institutional demand for stock is affected by firm-specific factors using both Tobit regression analysis and two different neural network methodologies. The neural networks are better able to capture nonlinear relationships between independent and dependent variables. Other studies have compared neural networks to standard statistical analysis. See Dasgupta, Dispensa, and Ghose (1994) and Wood and Dasgupta (1996) for such comparisons. The problem with using neural networks, however, is that they do not generate the usual coefficient estimates.[1] It can be difficult to evaluate the performance of the models. To overcome this problem we use the neural network models to predict future institutional ownership levels. By comparing the predictive capability of the neural networks to that of the linear model we are able to determine which performs best. Additionally, one of the neural network models automatically rejects input variables that do not improve the predictive capability of the network. By reviewing the variables retained, we gain some insight into which are important in a predictive sense.

This study provides a detailed examination of investment decisions made by large institutional investors. It is more comprehensive, uses a larger data set, and spans more years than any other study in this area. The results from this study also may shed light on the factors that determine institutional demand for stocks.

## THE DATA

The data set used in this study details the institutional ownership of about 3,000 firms for the years 1988 to 1991. This set of data provides an opportunity to examine those factors that may affect the demand for common stock. Prior research has done little in this area because the data needed to study individual investment demand are generally confidential and unavailable. Because the Securities and Exchange Commission requires institutional investors to disclose the contents of their investment portfolios, we now can examine the financial characteristics of the firms held in those portfolios to determine whether firm-specific factors result in greater ownership by institutional investors.

The data sample from which we extract the data set employed in this study includes all firms listed by Disclosure, Inc.[2] for the years 1988 through 1991. This sample includes firms listed on the New York Stock Exchange, the American Stock Exchange, or

[1] Neural networks do generate input weights but these are not synonymous with coefficient estimates and should not be used as such.

[2] We extend our thanks to Disclosure, Inc., for providing historical data for this study.

traded through the National Association of Security Dealers. The total number of observations ranges from 2,911 in 1988 to 3,351 in 1991.

Disclosure, Inc. reports data collected by Control Data Advisors Investment Technologies Spectrum 3/4. These data consist of the quarterly institutional ownership filings required by the Securities and Exchange Commission (SEC). All institutions with investment control of over $100 million must report quarterly to the SEC equity holdings above 10,000 shares and with market value above $200,000. The Disclosure data set used for this study includes all filings reported for December 31 of each sample year. Disclosure began reporting institutional ownership in 1988. The Spectrum files report for each firm the name of each institutional common stock investor and the number of shares which each institutional investor owns. One result of the SEC reporting requirements is that small institutional investors are not required to report portfolio composition. There are approximately 1,000 institutions reporting each year (which explains why the total institutional ownership level is lower than has been reported elsewhere). Additionally, the results of this study apply only to larger, more well-known institutions.

A review of the institutional ownership data reveals that some institutions report ownership interest in firms even when ownership is less than the 10,000 share cutoff. To be consistent across all institutions we eliminate any institutional ownership less than 10,000 shares.

All financial data used to calculate the ratios employed in this study are taken from the Compustat data set. After omitting those firms that do not report the data necessary to calculate the ten financial measures used in this study, our final data sample consists of 2,911 firms in 1988, 2,727 firms in 1989, 2,860 firms in 1990, and 3,351 firms in 1991. Sample statistics are reported in Table 1. In these years institutions held no investment in 482 firms in 1988, 427 firms in 1989, 389 firms in 1990, and 374 firms in 1991.

An examination of Table 1 provides some insight into the sample data. Institutional ownership is relatively low but increasing. Betas are positive and slightly above one. Current ratios are reasonable. Debt to asset ratios are low. Firms tend to be large based on market value. Price earnings ratios increase over the data span but are not unreasonable. Returns on asset ratios have negative means due to the existence of a number of smaller firms with significant losses. Small firms have equal weight with large firms in the calculation of the mean. The median indicates that typical ROA ratios are positive. Total and turnover is moderate. The firms shares are actively traded. Both mean net and operating profit ratios are negative due to the same factors as in the ROA ratios.

## THE FINANCIAL RATIOS USED IN THIS STUDY

We select a variety of firm specific characteristics and ratios to determine whether institutional investors appear to make common stock investments based on these characteristics. The set selected for investigation is influenced by data availability. Our final variable selection is discussed below and listed in Table 1.

PERCENT OWNERSHIP: The percentage shares held by institutions in each firm (PCTOWN) is computed by summing the number of shares held by institutions and dividing by the total number of shares outstanding.

## Table 1—Data Summary Statistics

| Panel A: 1988 (N = 2,911) | Mean | Median | Standard Deviation |
|---|---|---|---|
| Percent Institutional Ownership | .19 | .13 | .19 |
| Beta | 1.08 | 1.08 | .51 |
| Current Ratio | 2.59 | 1.99 | 2.27 |
| Debt to Asset Ratio | .18 | .15 | .18 |
| Log Market Value | 17.88 | 17.67 | 2.25 |
| Price Earnings Ratio | 8.61 | 10.57 | 17.32 |
| Return on Assets | -.06 | .09 | .87 |
| Total Asset Turnover | 1.00 | 1.01 | .05 |
| Trading Volume | .54 | .39 | .59 |
| Net Profit Margin | -.16 | .03 | 1.26 |
| Operating Profit Margin | -.13 | .06 | 1.12 |

| Panel B: 1989 (N = 2,727) | Mean | Median | Standard Deviation |
|---|---|---|---|
| Percent Institutional Ownership | .19 | .14 | .20 |
| Beta | 1.04 | 1.03 | .60 |
| Current Ratio | 2.59 | 1.98 | 2.23 |
| Debt to Asset Ratio | .19 | .15 | .20 |
| Log Market Value | 17.70 | 17.50 | 2.26 |
| Price Earnings Ratio | 8.03 | 10.29 | 18.35 |
| Return on Assets | -.07 | .07 | .92 |
| Total Asset Turnover | 1.00 | 1.01 | .05 |
| Trading Volume | .62 | .43 | .65 |
| Net Profit Margin | -.14 | .03 | 1.16 |
| Operating Profit Margin | -.11 | .06 | 1.00 |

| Panel C: 1990 (N = 2,860) | Mean | Median | Standard Deviation |
|---|---|---|---|
| Percent Institutional Ownership | .21 | .15 | .20 |
| Beta | 1.02 | 1.01 | .67 |
| Current Ratio | 2.47 | 1.88 | 2.22 |
| Debt to Asset Ratio | .19 | .15 | .20 |
| Log Market Value | 17.49 | 17.32 | 2.35 |
| Price Earnings Ratio | 7.95 | 8.98 | 17.49 |
| Return on Assets | -.14 | .06 | 1.09 |
| Total Asset Turnover | 1.00 | 1.01 | .05 |
| Trading Volume | .57 | .37 | .67 |
| Net Profit Margin | -.16 | .02 | 1.12 |
| Operating Profit Margin | -.13 | .05 | 1.06 |

| Panel D: 1991 (N = 3,351) | Mean | Median | Standard Deviation |
|---|---|---|---|
| Percent Institutional Ownership | .24 | .18 | .22 |
| Beta | 1.03 | 1.03 | .67 |
| Current Ratio | 2.48 | 1.87 | 2.17 |
| Debt to Asset Ratio | .18 | .13 | .19 |
| Log Market Value | 17.95 | 17.81 | 2.35 |
| Price Earnings Ratio | 9.07 | 11.56 | 19.97 |
| Return on Assets | -.13 | .06 | .99 |
| Total Asset Turnover | 1.01 | 1.01 | .04 |
| Trading Volume | .74 | .44 | .93 |
| Net Profit Margin | -.15 | .02 | .98 |
| Operating Profit Margin | -.09 | .05 | .88 |

$$(1)\ PCTOWN_i = \frac{\sum_{j=1}^{J} INSH_{ji}}{Shares_i}$$

where:

$PCTOWN_i$ = Percentage of shares owned by institutions in firm i;
$INSH_{ji}$ = Number of shares owned by institution j in firm i;
$Shares_i$ = Total number of shares outstanding in firm i.

NET PROFIT MARGIN (NPM): This ratio is calculated by dividing after tax net income by sales revenue. Investors should prefer higher NPM ratios.

OPERATING PROFIT MARGIN (OPM): This ratio is calculated by dividing operating profit by sales revenue. Investors should prefer high OPM ratios.

BETA: Provided by Compustat. It is computed using the S&P 500 index over the most recent 60 months. There is no theoretical basis to suggest whether institutional investors should prefer high or low betas. Several papers report that institutions prefer higher betas. For example, O'Brien and Bhushan (1990) find that beta is positively and significantly related to institutional ownership. Both Cready (1994) and Badrinath, Gay, and Kale (1989) report positive, significant coefficients when institutional ownership is regressed on beta. They conclude that institutions prefer higher risk firms. The finding that institutions prefer higher risk firms is not consistent with the position that institutions try to appear prudent. Shefrin and Statman (1995) investigate the relationship among stock returns to beta, firm size, and the book to market value ratio. They find that respondents in a Fortune survey of company reputations prefer large companies with low book to market ratios. They also find a negative and statistically significant relationship between beta and value, and a stronger negative relationship between standard deviation of returns and value.

CURRENT RATIO (CRNT): A high current ratio implies that the firm is liquid and is able to meet its current obligations. If institutional investors are influenced by the prudent investment hypothesis, they should prefer firms with high current ratios.

DEBT TO ASSET RATIO (DTOA): The debt to asset ratio measures a different aspect of firm risk. Higher levels of debt result in increased risk while also possibly increasing the rate of return. If institutional investors are concerned primarily with prudence, they should avoid firms with high debt to asset ratios. If institutional investors are primarily concerned with returns, they may prefer firms with a high debt to asset ratio.

MARKET VALUE (MRKVL): The log of total market value calculated as the number of common stock shares time the price per share. Larger firms usually are considered less risky than small firms because they tend to be more mature, are more closely tracked, have greater information flow, and have better access to the capital markets. If institutional investors are primarily concerned with returns, they may avoid large firms because there is substantial evidence that smaller firms provide greater returns. On the other hand, if institutions are primarily concerned with appearing prudent they may prefer investing in larger firms.

PE RATIO (PE): Firms with high PE ratios may be more risky than other firms because this implies that investors have optimistic expectations. By contrast, a low PE ratio may suggest that there is a problem with the firm that has depressed the price. We conclude that the prudent investor should choose securities with average PE ratios.

RETURN ON ASSETS (ROA): Investors should prefer firms with high return on assets. This implies greater operating efficiency and more effective management. A positive coefficient is predicted for ROA.

TOTAL ASSET TURNOVER (TAT): Total asset turnover (the ratio of sales to assets) measures how efficiently the firm generates revenue from assets. Presumably, investors prefer firms with high turnover rates.

TRADING VOLUME (TRDVOL): This ratio is calculated as the number of common shares traded per year divided by shares outstanding. We expect institutional investors to prefer firms with high trading volume for several reasons. Larger firms are likely to have greater turnover, and institutions may prefer large firms. Because institutions trade in large blocks, institutions may prefer firms with greater trading activity to avoid exerting price pressure when they buy or sell.

## METHODOLOGY

### REGRESSION USING TOBIT PROCEDURES

The current data set represents the best source of institutional ownership data available because it includes all reports of institutional ownership interest that are required by law. One problem exists—censoring occurs because SEC regulations exempt institutions from reporting shares held below a 10,000 share threshold and having a market value less than $200,000.

When data are censored, instead of observing y*, we actually observe y, which is defined as:

$$y_i = y_i^* \text{ if } y_i^* > C$$
$$= 0 \text{ if } y_i^* \leq C$$

where:

C = The level of censoring, in our case at the 10,000 share or $200,000 level.

Thus, the mean of $y_i$ is different than the mean of $y_i^*$, and the least square estimators are biased and inconsistent. The above model can be estimated using the procedures described in Tobin (1958).

We first estimate equation (2) using Tobit regression procedures.

$$(2)\ PCTIN = \alpha + b_1NPM + b_2OPM + b_3BETA + b_4CRNT + b_5TAT + b_6DTOA + b_7ROA + b_8PE + b_9MRKVL + b_{10}TRDVOL$$

The variables are as defined earlier. The estimated intercept and regression coefficients are used to forecast institutional ownership percentages in future periods.

### THE NEURAL NETWORK MODELS

Neural networks are becoming increasingly significant in the evaluation of economic relationships. Derived from the science of biological neurons, these techniques have been found useful in determining direct and hidden dependencies between not only explanatory variables and the variable(s) to be explained, but also factors that combine these indirect co-movements into various layers that will produce predictive success. In these networks processing elements combined into such layers between input and output layers are classified as *hidden* layers.

We examine the predictive power of both parametric and nonparametric models in this research effort. These models differ in their approach to both pattern recognition and prediction. Linear regression models are founded on assumed underlying distributions and resulting linear relationships. Neural networks make no assumptions regarding underlying distributions or linearity. As a result of these fundamental differences, the upward bias in calculated correlation coefficients found in linear regressions will not occur in the neural network models. This adds greater significance to our results, indicating higher predictive success using neural network models.

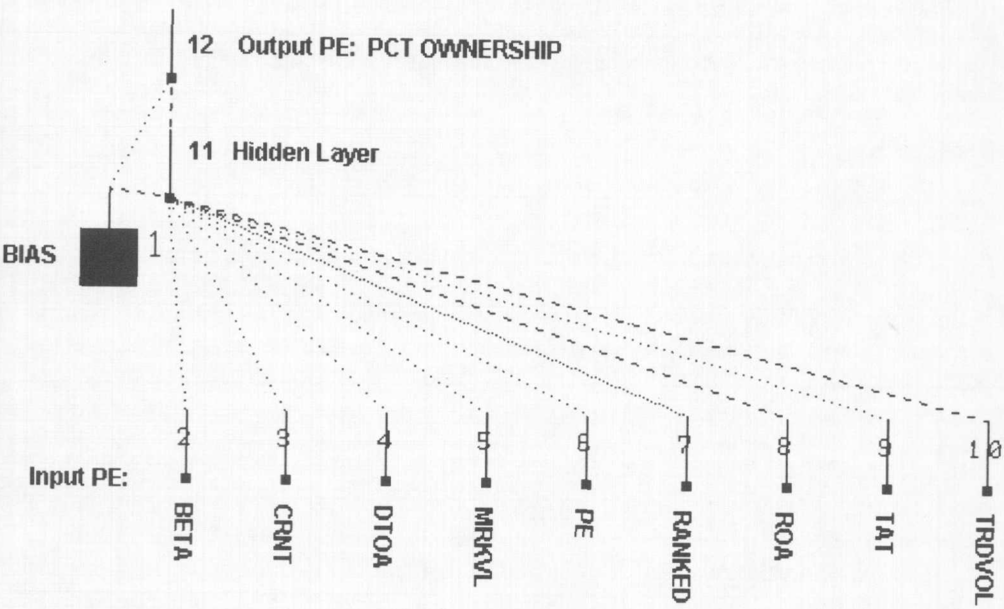
In the case where the output layer is known, the network selected will seek to create the best possible connection weights between input and desired output, thereby maximizing the explanatory power of the model. Data sets are typically separated into learning and testing groups. In this study we examine 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 hidden 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 nonparametric form of the network process, neural networks require no predetermined rules of behavior. 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 nonlinear multilayer network is produced that will combine the findings from all layers to yield the desired results. Neural nets often produce improved results and more robust models than those found in traditional models.

In this paper we compare the predictive ability of Tobit regression and the two neural network programs, one user controlled and one automatic.[3] The user-controlled neural network program (UCNN) requires a sequence of decisions to be made by the user to control the model building and analysis. The automatic neural network program (ANN) provides support by evaluating the user's objective function as a means to set all required network parameters, i.e., network parameters are evaluated by the software and set according to objective function success. Traditional neural network problems of overtraining or user errors in setting transformations are eliminated in this manner. The result of automatic neural network programs should be the best neural network model with accompanying parameters that achieve the objective of the research.

[3] In this study we employ two neural network programs designed by NeuralWare, Inc. The first is a user-controlled program called Pro II. The second is an automatic program called Predict. The Pro II model is referred to as a UCNN or user-controlled neural network. The Predict model is referred to as a ANN or automatic neural network.

**Figure 1—Neural Network Map**




## TYPE OF MODEL

A back-propagation (BP) model is a general purpose network that is well-suited for prediction and classification problems.[4] The back-propagation model used in this study is illustrated in Figure 1. As shown in Figure 1, we employ a set of ten firm level attributes as input variables, one hidden layer neuron, and one output variable (percent institutional ownership). With the objective function of minimizing global error in a nonlinear regression format, this model is often the first used in the development of a network system. Output can be in terms of a predictive model that is adaptable to other software applications. Using the back-propagation system developed in the user-controlled neural network model, the following parameters must be set.

## INPUT AND OUTPUT PROCESSING ELEMENTS

We use the nine previously discussed input variables (NPM, OPM, BETA, CRNT, TAT, DTOA, ROA, PE, MRKVL, TRDVOL) and one output variable (PCTOWN) in this study. The research procedure is to use prior year data to predict PCTOWN for the following year or years. The best model is defined to be that which has the highest predictive power. Our model employs ten input PEs and one output PE.

[4] Our efforts to use the user-controlled neural network model also involved extensive estimations of the models using back propagation, modular, and radial basis models. The standard back propagation models almost always yield the best results and are used in the final estimations reported in this paper.

## SELECTING THE NUMBER OF LAYERS AND INITIAL MODEL PARAMETERS

Several different forms of the network are estimated and tested. The typical back-propagation problem will have many input processing elements and one or more output PE elements. Three layers usually are found in back-propagation problems with one input, one hidden, and one output layer as the standard. We find that one hidden layer produces the best results.

## EPOCH SIZE SELECTION

The EPOCH size is the number of sets of training data used by the network between weight updates. It can make a significant difference in achieving the objective function of the model. This is especially true under circumstances where noise affects the learning rate of the system. The default value of this parameter is 16, indicating the number of interactions before any of the weights are updated by the model. Where there is more noise in the input stimuli the EPOCH size may be adjusted upward to the entire sample size of the learning data set. In our model we find an EPOCH size of 45 to 55 observations produces the best results.

## SELECTING THE LEARNING RULE

Various learning rules are available using user-controlled neural network. The rule selected will determine the process used in changing connection weights between input and output layers. All processing elements in a layer are affected by the same rule. In the selection of a rule, it is considered important first to consider the manner in which the learning data will be presented. In order to manage the problem of structured learning data sets, we find the cum delta rule to be the preferred learning rule. This variation on the delta rule model automatically adjusts weights to the order of data, which results in less weight sensitivity to the learning data set order of presentation and greater success in minimizing prediction error for similar test data sets.

## SELECTING THE TRANSFER FUNCTION

Transfer functions are available in this system of neural networks to transform the weighted sum of effective inputs that have been computed. This is an important parameter because it changes the system generated sum for each input PE to a potential output PE. Neuralware, Inc. User-controlled neural network requires the selection from a list that includes such functions as linear, sigmoid, tanH, DNNA, etc. The tanH transfer function is selected. It is widely used in back-propagation models, creating a continuous monotonic mapping of the input PEs into a range between plus one and minus one.

## IDENTIFYING THE LEARNING AND TESTING DATA SETS

We use learning and testing data sets that have one output processing element: PCTOWN. These data include learning files for years 1988 through 1990, with testing files from 1989 through 1991. In each case, raw data are used to test the model's ability to predict the next year institutional ownership using the current year data for learning. We conduct an exhaustive set of combinations of the above control settings in testing the user-controlled neural network.

The evaluation of the neural network models is particularly difficult. There is no way to determine the contribution of a particular input variable. Nothing analogous to regression coefficients and t-statistics can be calculated. The accuracies of the forecasts from these models are evaluated using the correlation coefficients between the actual and forecast values.

## RESULTS

The models (Tobit regression, user-controlled neural network, and automatic neural network program) are estimated and tested on both in-sample and out-of-sample data. The results are presented in Tables 2 through 6. The results from each model are discussed below.

### RESULTS OF THE TOBIT REGRESSIONS

Using the Tobit regression procedure, regressions of equation (2) are performed on the 1988, 1989, 1990, and 1991 data sets. The coefficients are reported in Table 2. Three of the variables (NPM, ROA, and PE) are generally not statistically significant at the $\alpha$ = .05 level. Five variables (BETA, CRNT, TAT, MRKVL, and TRDVOL) are significant in all years. The other variables have a mixed pattern. The statistically significant coefficients are all positive in sign, implying that institutional investors prefer high betas, high current ratios; high total asset turnover; larger firms; and high trading volume in all years. Cready (1994) also finds evidence that institutional investors prefer high BETA stocks. There is evidence that indicates investor preference for high debt ratios and higher operating profit margins.

**Table 2—Coefficients From Equation (2) Using Linear Regression**

| Variable | 1988 | 1989 | 1990 | 1991 |
|---|---|---|---|---|
| NPM | .0020169 | -.0051429 | -.0114878 | -.0108908 |
| OPM | .0043801 | .068215 | .0196677* | .017748* |
| BETA | .0388049* | .0204361* | .0216143* | .0346233* |
| CRNT | .0057992* | .0049415* | .0063272* | .0051997* |
| TAT | .3110988* | .3984844* | .3916481* | .4748668* |
| DTOA | .0363214 | .05905* | .0649985* | .0566491 |
| ROA | .0112737* | .0068658 | .0068277 | .0024118 |
| PE | .0001176 | .0003154 | .0000847 | .0002844 |
| MRKVL | .04844583* | .0478686* | .0500844* | .05776016* |
| TRDVOL | .0535116* | .0580999* | .0602846* | .0415223 |
| CONSTANT | -1.102735* | -1.166724* | -1.176258* | -1.382733* |
| N | 2,911 | 2,727 | 2,860 | 3,351 |

*Significant at the $\alpha$ = 0.05 level

In order to examine the stability of the model, we then use the constant term and coefficients from these regressions to forecast the PCTOWN for the years 1988, 1989, 1990, and 1991. The forecasts of PCTOWN are evaluated against the actual PCTOWN values for each year. The correlation coefficients between actual and forecast values are reported in Panel A, Tables 4, 5, and 6. The correlation coefficients from Table 4 are 0.559 for 1988; 0.572 for 1989; 0.606 for 1990; and 0.645 for 1991. These forecasts provide benchmark estimates derived from a linear model.

**Table 3—Variable Transformations Used in the PREDICT Models**

| Variable | 1988 | 1989 | 1990 | 1991 |
|---|---|---|---|---|
| BETA | Fuzzy Right | Fuzzy Right | Fuzzy Right | Fuzzy Right |
| CRNT | Fuzzy Left | Fuzzy Left | Fuzzy Right | TanH |
| TAT | Fuzzy Right | Fuzzy Right | Fuzzy Left | Fuzzy Right |
| DTOA | Linear | Fuzzy Left | Fuzzy Left | Fuzzy Left |
| ROP | Fuzzy Right | Fuzzy Right | Fuzzy Right | Fuzzy Right |
| PE | TanH | TanH | Power2 | Linear |
| MRKVL | Linear | Linear | TanH | TanH |
| TRDVOL | Linear | Fuzzy Left | Fuzzy Left | Fuzzy Left |
| NPM | Fuzzy Right | Fuzzy Right | Fuzzy Right | Fuzzy Right |
| OPM | Fuzzy Right | Fuzzy Right | EXPEXP | TanH |
| PCTOWN | Log | Log | Log | Log |

Linear = Identity function
Log = Natural logarithm function
LogLog = Log of Log
Exp = Exponential function
Pwr2 = Square function
Pwr4 = Fourth power function
Rt2 = Square root function
Rt4 = Fourth root function
Inv = Inverse function (1/x)
InvPwr2 = 1.0/(square function)
InvPwr4 = 1/0/(fourth power function)
InvRt2 = 1.0/(square root function)
InvRt4 = 1.0/(fourth root function)
TanH = Hyperbolic tangent function
In x/(1-x) = Log (x/(1-x))

The estimates in Panel A, Table 4 are probably biased upward because the tests are performed on the same data used to perform the estimates. We next conduct true out-of-sample tests. A regression of equation (2) on 1988 data is estimated and tested on 1989 data. In similar fashion, a regression is estimated on 1989 data and tested on 1990 data and estimated on 1990 data and tested on the 1991 data. The results are reported in Panel A, Table 5. The correlation coefficients between forecast and actual values are 0.569 for 1989; 0.606 for 1990; and 0.640 for 1991. These results show little difference from forecasts performed with the within-sample tests of the model shown in Panel A, Table 4.

In an effort to examine long-term forecast accuracy, the constant term and coefficients from the 1988 estimates are used with the 1989, 1990, and 1991 data to forecast PCTOWN for those three years. The forecasts are compared to the actual data, and correlation coefficients are calculated to assess the forecast accuracy. The results are presented in Panel A, Table 6. The correlation coefficients are 0.569 for 1989; 0.602 for 1990; and 0.639 for 1991. This represents a rigorous test of the model because in one case we are forecasting as much as three years in the future. The forecast accuracy is virtually identical to the short-term forecasts.

The results indicate that approximately 60 percent of institutional investment decisions can be explained by the financial ratios using Tobit regression. We next use the two neural network models to try to improve these results.

**Table 4—Results Using In-Sample Tests on Same Data**

Panel A: Tobit Regression Results

| Model Estimated On | Tested On | Correlation Coefficient |
|---|---|---|
| 1988 Data | 1988 Data | 0.559 |
| 1989 Data | 1989 Data | 0.572 |
| 1990 Data | 1990 Data | 0.606 |
| 1991 Data | 1991 Data | 0.645 |

Panel B: PRO II Neural Network Model

| Model Estimated On | Tested On | Correlation Coefficient |
|---|---|---|
| 1988 Data | 1988 Data | 0.6813 |
| 1989 Data | 1989 Data | 0.6345 |
| 1990 Data | 1990 Data | 0.6652 |
| 1991 Data | 1991 Data | 0.6901 |

Panel C: PREDICT Neural Network Model

| Model Estimated On | Tested On | Correlation Coefficient |
|---|---|---|
| 1988 Data | 1988 Data | 0.6951 |
| 1989 Data | 1989 Data | 0.7121 |
| 1990 Data | 1990 Data | 0.7223 |
| 1991 Data | 1991 Data | 0.7462 |

**Table 5—Results Using One Year Ahead Forecasts**

Panel A: Tobit Regression Results

| Model Estimated On | Tested On | Correlation Coefficient |
|---|---|---|
| 1988 Data | 1989 Data | 0.569 |
| 1989 Data | 1990 Data | 0.606 |
| 1990 Data | 1991 Data | 0.640 |

Panel B: PRO II Neural Network Model

| Model Estimated On | Tested On | Correlation Coefficient |
|---|---|---|
| 1988 Data | 1989 Data | .5886 |
| 1989 Data | 1990 Data | .6422 |
| 1990 Data | 1991 Data | .6814 |

Panel C: PREDICT Neural Network Model

| Model Estimated On | Tested On | Correlation Coefficient |
|---|---|---|
| 1988 Data | 1989 Data | .7621 |
| 1989 Data | 1990 Data | .7443 |
| 1990 Data | 1991 Data | .7392 |

## RESULTS OF THE USER-CONTROLLED NEURAL NETWORK MODEL ESTIMATIONS

We employ the same sequence of tests with the user-controlled neural network model. First, we estimate separate models using the 1988 data and testing it on the 1988 data, estimating the regression on the 1989 data and testing on the 1989 data, etc. The correlation coefficients between the estimated and actual PCTOWN are reported in Panel B, Table 4. The correlation coefficients are 0.6813 for 1988; 0.6345 for 1989; 0.6652 for 1990; and 0.6901 for 1991. These are significantly better than those from the Tobit regression model shown in Panel A, Table 4.

In order to test the forecasting ability of the user-controlled neural network models on out-of-sample data we estimate models on the 1988 data and test on the 1989 data, esti-

**Table 6—Results Using Long-Term Forecasts**

Panel A: Tobit Regression Results

| Model Estimated On | Tested On | Correlation Coefficient |
|---|---|---|
| 1988 Data | 1989 Data | 0.569 |
| 1988 Data | 1990 Data | 0.602 |
| 1988 Data | 1991 Data | 0.639 |

Panel B: PRO II Neural Network Model

| Model Estimated On | Tested On | Correlation Coefficient |
|---|---|---|
| 1988 Data | 1989 Data | .5289 |
| 1988 Data | 1990 Data | .6121 |
| 1988 Data | 1991 Data | .6679 |

Panel C: PREDICT Neural Network Model

| Model Estimated On | Tested On | Correlation Coefficient |
|---|---|---|
| 1988 Data | 1989 Data | .6883 |
| 1988 Data | 1990 Data | .7992 |
| 1988 Data | 1991 Data | .8210 |

mate new models on the 1989 data and test on the 1990 data, etc. The correlation coefficients between the forecast and actual ownership percentages are reported in Panel B, Table 5. The correlation coefficients are 0.5886 for 1989; 0.6422 for 1990; and 0.6814 for 1991. The Tobit regression correlation coefficients in Panel A, Table 5 are not as large as those of the user-controlled neural network model shown in Panel B.

In an effort to more rigorously test the model's forecasting ability, we first estimate the model on 1988 data and then successively test it on the 1989, 1990, and 1991 data. Thus, we are forecasting ownership percentage as much as three years in the future. The results are shown in Panel B, Table 6. The correlation coefficients are 0.5289 for 1989; 0.6121 for 1990; and 0.6679 for 1991. The user-controlled neural network model results are generally slightly better than the Tobit regression results.

## RESULTS FROM THE AUTOMATIC NEURAL NETWORK PROGRAM MODEL ESTIMATIONS

The automatic neural network program model automatically tests different transformations on each variable and selects those transformations that add to the explanatory power of the model. Those transformations employed in the models are listed in Table 3.

The automatic neural network model first is estimated using the 1988 data and testing on 1988 data, etc. The correlation coefficients between the estimated and actual institutional ownership shown in Panel C, Table 4 percentage are 0.6951 for 1988; 0.7121 for 1989; 0.7223 for 1990; and 0.7462 for 1991. The estimates are significantly better than those from the Tobit regression model. The results suggest that the financial variables employed in this study measure effects that are important in decisions made in the open market.

The automatic neural network program model next is estimated on 1988 data and used to forecast 1989 data, estimated on 1989 data and used to forecast 1990 data, and estimated on 1990 data and used to forecast 1991 data. The results are shown in Panel C, Table 5. The correlation coefficients are 0.7621 for 1989; 0.7443 for 1990; and 0.7392 for 1991.

These results are better than those for the Tobit model shown in Panel A or those for the user-controlled neural network model shown in Panel B.

The automatic neural network program model next is estimated on 1988 data and used to forecast the 1989, 1990, and 1991 data. The results are shown in Panel C, Table 6. The correlation coefficients are 0.6883 for 1989; 0.7992 for 1990; and 0.8210 for 1991. These results are superior to the Tobit model results shown in Panel A or the user-controlled neural network model results shown in Panel B.

## CONCLUSIONS

The results of this study indicate that institutional investors consider individual firm financial attributes in making investment decisions. We find that nonlinear neural network models generated by the automated automatic neural network program significantly outperform either the user-controlled neural network or the Tobit regression program.

Other studies such as Cready (1994) have examined investor behavior. Cready concludes that among individual investors the demand for riskier, larger, and low dividend stocks is a positive function of wealth. He finds that institutional investors prefer larger firms, S&P 500 firms, and firms with low dividend yields.

Daniel and Titman (1997) examine the relationship between stock returns and various financial and risk measures. They find that traditional risk measures do not determine expected returns. The CAPM beta is found to have no returns predictive power even after controlling for firm size and book-to-market ratios. Their results seem to indicate that expected returns are based on firm characteristics rather than risk as it is typically measured.

In a broad sense, our results indicate that institutional investment decisions are not guided solely by the marginal effect of an investment on a portfolio. Instead, individual firm attributes appear to influence investment decisions.

## REFERENCES


1. Badrinath, S.G., G.D. Gay, and J.R. Kale, "Patterns of Institutional Investment, Prudence, and the Managerial 'Safety Net' Hypothesis," *The Journal of Risk and Insurance*, LVI, no. 4 (December 1989), pp. 605-629.

2. Cready, W.M., "Determinants of Relative Investor Demand for Common Stocks," *Journal of Accounting, Auditing and Finance*, 9, no. 3 (Summer 1994), pp. 487-507.

3. Daniel, K., and S. Titman, "Evidence on the Characteristics of Cross Sectional Variation in Stock Returns," *Journal of Finance*, 52, no. 1 (1997), pp. 1-33.

4. Dasgupta, C.G., G.S. Dispensa, and S. Ghose, "Comparing the Predictive Performance of a Neural Network Model With Some Traditional Market Response Models," *International Journal of Forecasting*, 10 (1994), pp. 235-244.

5. Del Guercio, Diane, "The Distorting Effect Of The Prudent-Man Laws On Institutional Equity Investments," *Journal of Financial Economics*, 40 (1996), pp. 31-62.

6. Dowen, R.J., and W.S. Bauman, "A Fundamental Multifactor Asset Pricing Model," *Financial Analysts Journal* (July 1986), pp. 45-51.

7. Falkenstein, E.G., "Preferences for Stock Characteristics as Revealed by Mutual Fund Portfolio Holdings," *Journal of Finance*, 51, no. 1 (1996), pp. 111-136.

8. Fama, E.F., "Stock Returns, Real Activity, Inflation, and Money," *American Economic Review*, 71 (1981), pp. 545-565.

9. Fama, E.F., and K.R. French, "Dividend Yields and Expected Stock Returns," *Journal of Financial Economics*, 22 (1988), pp. 3-25.

10. Fama, E.F., "The Cross-Section of Expected Stock Returns," *The Journal of Finance*, 47 (1992), pp. 427-465.

11. Fama, E.F., "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics*, 33 (1993), pp. 3-56.

12. Fama, E.F., and K.R. French, "Size and Book-to-Market Factors in Earnings and Returns," *The Journal of Finance*, 50, no. 1 (March 1995), pp. 131-155.

13. Hessel, C.A., and M. Norman, "Financial Characteristics of Neglected and Institutionally Held Stocks," *Journal of Accounting Auditing & Finance*, 7, no. 3 (Summer 1992), pp. 313-334.

14. O'Brien, P.G., and R. Bhushan, "Analyst Following and Institutional Ownership," *Journal of Accounting Research,* 28 (Supplement 1990), pp. 55-76.

15. Shefrin, H., and M. Statman, "Making Sense of Beta, Size, and Book-to-Market," *The Journal of Portfolio Management* (Winter 1995), pp. 26-34.

16. Tobin, J., "Estimation of Relationships for Limited Dependent Variables," *Econometrica*, 26 (1958), pp. 24-36.

17. Wood, D., and B. Dasgupta, "Classifying Trend Movements In The MSCI U.S.A. Capital Market Index—A Comparison Of Regression, Arima And Neural Network Methods," *Computers Options Research*, 23, no. 6 (1996), pp. 611-622.