Predicting Corporate Acquisitions: An Application of Uncertain Reasoning Using Rule Induction

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ABSTRACT

Artificial Intelligence (AI) -based rule induction techniques such as IXL and ID3 are powerful tools that can be used to classify firms as acquisition candidates or not, based on financial and other data. The purpose of this paper is to develop an expert system that employs uncertainty representation and predicts acquisition targets. We outline in this paper, the features of IXL, a machine learning technique that we use to induce rules. We also discuss how uncertainty is handled by IXL and describe the use of confidence factors. Rules generated by IXL are incorporated into a prototype expert system, ACQTARGET, which evaluates corporate acquisitions. The use of confidence factors in ACQTARGET allows investors to specifically incorporate uncertainties into the decision making process. A set of training examples comprising 65 acquired and 65 non-acquired real world firms is used to generate the rules and a separate holdout sample containing 32 acquired and 32 non-acquired real world firms is used to validate the expert system results. The performance of the expert system is also compared with a conventional discriminant analysis model and a logit model using the same data. The results show that the expert system, ACQTARGET, performs as well as the statistical models and is a useful evaluation tool to classify firms into acquisition and non-acquisition target categories. This rule induction technique can be a valuable decision aid to help financial analysts and investors in their buy/sell decisions.

Key Words: Mergers & Acquisitions, Rule Induction, Machine Learning, Expert Systems, and Uncertain Reasoning.

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1. INTRODUCTION

The market for corporate control is represented by equity markets where ownership claims on firms are bought and sold. If decision making under uncertainty characterizes routine trading of securities, the degree of uncertainty is compounded during mergers and acquisitions (M&A) transactions, with potential for heightened conflicts of interest between shareholders, managers, debt holders and other public. In cases involving multiple bidders, the dynamics get even more complicated and interesting. Industry and firm specific attributes, changes in risk-aversion and perception of investors, agency problems of managers, shareholders, debt providers, and employees all make the field of M&A an excellent arena for business applications of uncertain reasoning.

Research shows that shareholders of acquired firms, on average, receive significant share price gains while the share price increases for acquiring firms are much smaller (Copeland and Weston 1998). Galai and Masulis (1976) argue that corporate acquisitions tend to transfer wealth from shareholders to bondholders. Academic researchers have developed several statistical models (regression, correlation analysis, discriminant analysis, logit, etc.) to predict corporate acquisitions or takeovers (see Akhigbe and Madura, 1999; Cudd and Duggal, 2000; and Palepu, 1986). However, these statistical models use only objective information and ignore relevant subjective information. Also, statistical models assume multivariate normality and homoscedastic variances, assumptions routinely violated in real world data. In view of these constraints with statistical models, computer-based expert systems (ES) have been touted as viable alternatives for decision making in the fields of finance, accounting and marketing (Liang 1992; Nikolopoulos 1997). Under certain circumstances ES can perform better than standard statistical models and can be used as valuable decision aids (Messier and Hansen 1988; Liang 1992; Ragothaman, Carpenter, and Naik 1995).

The objective of this paper is to illustrate a finance application of uncertain reasoning in a machine learning program (IXL - Induction on eXtremely Large databases, IntelligenceWare, 1992) and compare the predictive ability of IXL with the results of discriminant analysis and logit models. We compare financial ratios of firms that were acquired and those that were not (control firms). We also describe the use of confidence factors to handle uncertainty and the use of "fuzzy topology" and "inexact neighborhood" concepts to capture uncertainty. The remainder of the paper is organized into the following sections. Section 2 discusses the motivation for the work, followed by a review of the prior research and explanation for the variables used in the study. The process of discovering rules using IXL and how uncertainty is handled in IXL are described in section 3. The expert system development process and confidence factors to capture uncertainty are described in section 4. The fifth section contains the results of the statistical and expert system models and a discussion of the comparative performance of the different approaches in predicting acquisition target firms. A summary of the application of uncertain reasoning in decision making with respect to mergers and acquisitions is presented in section 6.

2. MOTIVATION AND PRIOR RESEARCH

The market for corporate control is an active and vibrant one, especially in the United States. M&A activity in the US came in identifiable waves in the last century starting with largely horizontal consolidation types (1897-1904) and continuing with industry concentration mergers (1916-1929). The stock market crash in 1929 and Clayton Act restricting monopolistic practices ended that wave. 1965-69 saw the prevalence of the conglomerate type mergers as firms sought to grow earnings through acquisitions that also tended to reduce variability of cash flows. Unlike earlier mergers, these did not result in significant increases in concentration within industries. Corporate diversification fell out of favor, with improved understanding of the role and pricing of risk and the ability of shareholders to diversify risk in well functioning capital markets. The 1980s witnessed large scale divestment activities as conglomerates were broken up. The period from 1992 has been characterized by a sharp increase in the number and size of M&A transactions, and this period has been called the *age of the mega-merger* (DePamphilis 2001).

Understandably, the flurry of M&A activities has been accompanied by a stream of research aimed at understanding their causes and effects. The ability to identify potential M&A candidates is of interest to a wide range of participants, including *equity investors* who see the large rewards (and risks) involved and *corporate management* with the mandate to enhance shareholder values while protecting their own jobs, wealth and reputation. Other interested parties include *employees* concerned about the stability of the firms they work for and potential disruptive effects on their jobs, *state and local governments* exposed to the tax and job creation/destruction effects of corporate restructuring and the impact of legislation on the competitiveness of their states in attracting corporate investments, and *investment banks* for identifying potential targets and funding such activity.

Prior Research

Research attempts to predict the likelihood of being acquired have become more sophisticated as our understanding of the phenomenon improved. Different variables suggested by theory were tested, and differing methodologies and control techniques were used to isolate the effects of the variables of interest. The underlying thread in all the cited research below, is that of the *shareholder wealth maximization through increasing firm value.* The variables identified by only a few important empirical studies are discussed in this section.

Firms with excess free cash flows tend to be undervalued by the market to reflect inefficiencies induced by potential conflict of interests between shareholders and managers with access to the free cash flows and a tendency not to disgorge the excess cash. Resulting excess financial slack may cause managers to invest in projects that return less than the cost of capital or to waste it in organizational inefficiencies (Jensen, 1986). Another impact is the increased likelihood of the firm becoming a takeover target, since acquiring firms can use the excess liquidity to pay off some of acquisition costs. Therefore, once a firm becomes a target, other firms in the industry are also likely targets - the larger the financial slack in a firm, the greater the likelihood of that firm becoming a takeover target. These dynamics cause a corresponding increase in prices of such firms in an industry. Akhigbe and Madura (1999) confirm these hypothesized effects. Our variables *cash flow to sales* and *current ratio* (liquidity measure) aim to capture these effects.

Morck, Schlieffer, and Vishny (1988) found market/book value ratios along with size to be good predictors. Size was also found to be a good predictor by Comment and

Schwert (1995). Shivdasani (1993) found that size, managerial holdings and affiliate firm cross-holdings were good predictors while earnings growth and board composition (independent v/s employee or family members) were poor predictors. Market/Book value has been used as a measure of managerial efficiency as well as an indicator of over/under valuation for firms. Our variables *Market Values* and *Market/Book Value Ratios* are based on these and other findings of significance for size and degree of undervaluation and inefficiencies.

Fixed Tangible Assets support debt capacity since they typically retain value better than intangible assets if a firm goes through liquidation. Firms with higher tangible to total asset ratios have been found to be more attractive acquisition targets (Copeland and Weston 1998). Firm's growth is also expected to be positively related to the probability of acquisition. Since growing firms often undertake capital expenditures to support the growth, our *capital expenditures to total assets* ratio provides a composite proxy measure for growth and asset intensity of firms**.**

Cudd and Duggal (2000) adjust for distributional properties of the variables used to operationalize six acquisition hypotheses in predicting takeover targets. Using Logit analysis, they find that their post adjustment model results are consistent with four of the six acquisition hypotheses (up from one in the pre-adjusted model). Their adjusted model produced 76.1 % classification accuracy – largely driven by its ability to predict unacquired firms. The variables identified as significant predictors of takeover likelihood are size, return on equity, a growth-resources-mismatch dummy variable, and industry disturbance dummy variable (proxy for M&A activity during the prior 12 months). Neither market/book value nor price/earnings ratio variables were found to be significant in this study.

Price/earnings ratio has been found to capture market's growth expectations for a firm/industry and the quality of earnings effect. We have also used price/earnings ratios as a variable of interest in our study**.** Capital structure is an important policy decision. There is agreement on the existence of an optimal capital structure once we account for the tax-subsidy on debt financing (*interest payments being tax deductible)*, increased bankruptcy risk, costs of financial distress, and the agency problems that arise from excessive use of debt financing. Theodossiou, Kahya, Saidi and Philippatos (1996) find that, for financially-distressed firms, leverage and insider control are negatively related to the probability of acquisition. Firms operating much outside the optimal capital structure prescriptions are typically undervalued and thus become attractive takeover targets. This undervaluation is a relatively easy fix, as the acquiring firm can either un-lever or re-lever the acquired firm to bring it to the optimal financing mix and obtain increased valuation. Our *debt to equity ratio* variable captures the leverage effect**.**

Risk and pricing of risk underlie most of the valuation models used in finance. The importance of the systematic portion of risk as being the non-diversifiable and therefore priced element is exemplified by the Capital Asset Pricing Model, the dominant valuation model. This model represents the relationship between the systematic risk measure, beta, and expected return on an investment (first proposed independently by Lintner(1965) and Sharpe (1964). We use *beta* to account for the effect of non-diversifiable risk on the probability of takeovers**.**

3. MACHINE LEARNING IN KNOWLEDGE DISCOVERY

One problem with knowledge acquisition is that it can consume a great deal of time and effort (Michalski and Chilauski, 1980) and often results in inconsistent rules. Biggs, Messier and Hansen (1987) found that it was difficult to extract production rules from protocols obtained from experts. The problems inherent in this tedious process of identifying production rules from transcriptions of protocols have often prevented timely development of expert systems. In order to overcome this knowledge acquisition bottle-neck, researchers have suggested alternative approaches. One such approach is to use rule induction techniques. In this project, we use a commercially available rule induction technique called, Induction on eXtremely Large (IXL) databases (IntelligenceWare 1991). IXL is implemented in a subsequent updated software by IntelligenceWare called "IDIS" (Information Discovery System), which is used in this research (IntelligenceWare 1994).

"Machine learning" has been used in a variety of artificial intelligence applications. For example, one application of machine learning involves adaptive systems that monitor their own performance and attempt to improve it by adjusting internal parameters. Another application of machine learning involves the discovery of knowledge contained in databases (Quinlan 1986). Knowledge discovery has been defined as the "nontrivial extraction of implicit, previously unknown, and potentially useful information from data" (Frawley, Piatetsky-Shapiro, and Matheus 1991). The knowledge is often extracted in the form of decision trees or production rules using inductive learning.

Inductive learning can be defined as the process of inferring the description of a class of objects from the description of the individual objects of the class (Shaw 1987). For example, in this research, the set of firms that were acquired can be considered as a class of objects. Each individual firm included in the set is an object of the class. Thus, we have two classes corresponding to the two sets of firms, those that are acquisition targets and those that are not. Each class is described by a class recognition rule as a result of inductive learning. If an object possesses attributes that satisfy this rule, then it is assumed to represent the given class. A class recognition rule can be written in the format of a production rule or IF-THEN rule. An example of such a rule is given next:

IF		Firm's current ratio is Medium
	AND	Firm's capital intensity is High
THEN		The result = acquisition target

Parsaye and Hansson (1987) described an approach to machine learning which is implemented in a proprietary machine learning software package called IXL (IntelligenceWare 1991). IXL provides a software environment with a number of helpful features such as windows, pop-up menus, and buttons that make the use of this program easy. The software has been used by a number of organizations in a variety of applications such as financial market analysis, discovery of patterns in radar deployment, complex scientific analysis related to catalysts and crystallization process, commercial lending by banks, and oil exploration (IntelligenceWare 1992).

Parsaye, Chignell, Khosafian, and Wong (1989) claim that IXL is a better machine learning system than ID3 (an earlier machine learning program). Unlike ID3, which induces a decision tree, IXL induces production rules directly. Although a decision tree can be translated into production rules, mutual exclusivity of rules is inherent in tree induction. Weiss and Kulikowski (1991, p. 133) state that the production rule format is potentially more powerful than the decision tree format, and that the relaxation of restrictions on mutual exclusivity of rules can potentially lead to coverage of classes more efficiently. However, they also explain that there could be problems in using disjunction (OR) in a set of nonmutually exclusive rules. IXL produces nonmutually exclusive rules. However, it uses only conjunction (AND) of clauses in the rules generated. In this research, IXL was used primarily because of the availability of the software and the user-friendly software environment of IDIS. A brief description of IXL and the induction principles employed in it are presented next.

Rule Induction Using IXL

The IXL environment consists of five modules: the User Interface, the Data Dictionary, the Discovery Module, the Induction Engine, and the Database Interface (Parsaye and Hansson 1987; Parsaye, Chignell, Khosafian, and Wong 1989). The Discovery Module searches the database to reveal interesting patterns and relationships. Statistical techniques such as correlation and other machine learning techniques are used in this module to analyze the data. The search process may be guided by specifying discovery parameters. Detailed descriptions and the capabilities of IXL and the discovery features can be found in IntelligenceWare (1991). The Induction Engine constructs topological neighborhoods for the relevant records and then performs generalization on these neighborhoods to discover rules (Parsaye and Hansson 1987).

IXL is used to generate a set of production rules or IF-THEN from a set of training examples. Thus, the first step in knowledge discovery using IXL is to prepare a database of training examples. A training example is a set of financial attribute values for a firm and its status (i.e. whether acquired or not). A training example is represented as a single record in a database. The attributes are represented as the fields of a record. Once the database file is created, the next step is to specify it as input to IXL. If the entire database file is not used, then a random sample of the specified size is automatically selected by IXL. In this research, the entire database file was used for knowledge discovery due to the limited size of the database. Less than 100 percent of the database is generally used in the case of very large databases to save computational time, to avoid over-fitting, and to allow for a holdout sample. The third step in using IXL is to specify the discovery goal for the rules to be generated. IXL specifying the interest level of the investigator corresponding to each of the attributes that will be used in the antecedent (the IF part) of a production rule (IF-THEN rule). In this research, equal interest level was specified for each attribute in the absence of information to specify varying interest levels.

The final step in knowledge discovery involves specifying a number of discovery parameters that allows IXL to tailor its performance to best suit the objective of the investigator. These discovery parameters include the minimum number of records involved in a rule formation, the minimum level of confidence in forming a rule, the maximum level of error permissible in estimating the rule confidence level, and the maximum rule length (number of clauses in the IF part). Detailed explanations of these discovery parameters are available in IntelligenceWare (1991). A maximum rule length of 4 was considered to be appropriate in this research. Rules with clauses more than 4 were considered to be overspecialized and undesirable. However, rules with less number clauses (for example, one or two) were accepted even though they may be somewhat overgeneralized.

The problem of dealing with continuous ranges of numerical values in the rules generated by induction has been previously encountered by other researchers (Srinivasan and Kim 1988, Ziarko 1991, Chan and Wong 1991, Ragothaman and Naik, 1994). One way of dealing with this problem is to replace the continuous numeric values with discrete ranges with qualitative labels. Such a transformation seems to make the patterns in the data more discernible and easier to characterize in terms of rules (Srinivasan and Kim 1988, Ziarko 1991, and Chan and Wong, 1991). Therefore, the authors decided to transform the continuous numerical values of the data into discrete categories labeled as "Very High", "High", "Medium", "Low", and "Very Low". The authors subjectively defined these ranges after sorting the numerical values of an attribute variable present in the database and after visually examining the clusters of numbers. For example, values of capital expenditures to total assets ratio less than 0.02 were categorized as "Very Low", values between 0.02 and 0.05 as "Low", values between 0.05 and 0.08 values as "Medium", values between 0.08 and 0.17 as "High", and values that are more than 0.17 as "Very High". The cut-off points for the ranges defined for the variables are presented in Table 1. A database with the discretized categories of the variables was created from the training sample, and was used as input to IXL. The rules generated by IXL used these categories to specify the values of attribute variables.

[Insert Table 1 here]

Uncertainties in the database and IXL-generated confidence factors

Since IXL is a proprietary and commercial software, the details of the technique or the algorithms used for rule induction have not been published by the designers of the software. However, the designers provided a technical report (Parsaye and Hansson 1987), which gives an indication of the principles used in IXL. According to Parsaye and

Hansson (1987), the technique used in IXL is a method of "inexact deductive induction" that is based on "fuzzy topology" treated by Postin (1974). They also state that Postin (1974) defined "fuzzy topology" in terms of "inexact neighborhoods" following earlier published works in the field of topology including those of Menger (1953). In short, the application of "fuzzy topology" to a database results in a series of local comparisons between specific records in a database until a global pattern emerges from the data similar to what is achieved by other methods of induction (Parsaye and Hansson 1987).

An example of the rules induced by IXL is given below:

```
Rule 10
        CF = 100%

                "CLASS" = "ACQUIRED FIRM"

        IF
                "current_ratio"             = "medium"
        AND
                "cashflow_sales_ratio"      = "very_low"
        AND
                "price_to_earnings_ratio"   = "medium"

        Margin of error: 5.0 %
        Applicable percentage of sample: 7.69 %
        Applicable number of records: 10
```

This rule indicates that 7.69 percent of the database or 10 records were used in generating it. The term "CF" indicates the confidence factor of this particular rule. The margin of error indicates the extent to which the stated confidence factor may deviate. For example, the confidence factor of this rule may vary by 5 percent above or below the stated CF. However, in this case the stated CF is 100 percent. Since the value of CF cannot exceed 100 percent, the feasible range for the CF is from 95 to 100 percent. The number of records in the database that generated this rule is 10, which is 7.69 % of the database. IXL generates confidence factors to capture uncertainty present in the training sample. Other researchers have used a variety of schemes to handle uncertainty in AI including Bayes nets (Pearl 1989), belief function formalism (Srivastava and Datta 2002), fuzzy logic (Zadeh 1983) and valuation-based systems (Shenoy, 1992). The nature of the confidence factors (CF) generated by IXL is explained in the following section.

The confidence factor of a rule generated by IXL states the degree of certainty with which a firm may be regarded as belonging to the class "Acquired Firm" when the attribute values of the firm match with those described by the "AND" clauses in the "IF" part of the rule. The source of the uncertainty which determines the value of "CF" of a rule generated by IXL is present in the inconsistencies inherent in the training examples contained in the database. Generating a rule through a process of generalization from a limited number of training examples will most likely yield a range for the confidence factor. This range is specified by indicating a margin of error. In general, the "CF" of a rule generated by IXL is an indication of the quality of the rule. In the next section, we describe the creation of the prototype expert system, ACQTARGET.

4. BUILDING THE PROTOTYPE EXPERT SYSTEM, ACQTARGET

A commercially available expert system shell, VP-Expert was used to build the prototype system, ACQTARGET. VP-Expert was chosen because of its modularity and the ease with which the knowledge base can be built and refined. Other advantages of VP-Expert include its ability to read a variety of data files such as dBase, ASCII, Excel, and Lotus files, and its ability to perform sensitivity analysis. VP-Expert can incorporate uncertainty by using user-supplied confidence factors. It can support math functions, chain knowledge bases, call external programs, induce decision tables, and it features an excellent user interface (Gray 1988). It has also been previously used in academic research (Nelson and Balachandra 1991; Ragothaman, Carpenter and Naik 1995).

The knowledge-base in ACQTARGET consists of "IF.. THEN" production rules. These production rules were generated from a database using IXL. The database used in this research was obtained from COMPUSTAT. A sample of 97 firms that were acquired was obtained from news-items in the Wall Street Journal during 1994 through 1996. The data for the control sample of 97 non-acquisition firms was also obtained from COMPUSTAT. The database of 97 acquisition and 97 non-acquisition firms was divided into two groups of samples. A training sample of 65 acquisition firms and 65 non-acquisition firms was selected randomly for the purpose of rule induction using the machine learning program IXL. The remaining 32 acquisition firms and 32 non-acquisition firms formed the validation sample. The expert system, ACQTARGET, was built using the rules induced from the training sample. It was then used to evaluate and classify the firms in the validation sample. Each record in the database represents a firm and contains nine fields corresponding to nine selected attributes of the firm. These attributes are: 1) current ratio, 2) cashflow to sales, 3) capital expenditures to total assets, 4) Square-root of market value, 5) beta, 6) market to book ratio, 7) price/earnings ratio, 8) debt to equity ratio, and (9) acquisition code (ACQCODE) indicating whether the firm is an acquisition or a non-acquisition case. If a variable for a firm was missing, the series average was used in its place.

Table 2 presents Pearson product moment correlations for all explanatory variables. This table indicates that explanatory variables are only slightly correlated with each other. A rule of thumb is suggested by Judge et al. (1980, pp.459) to assess the impact of multicollinearity. They argue that a serious multicollinearity problem arises only when the correlations among the explanatory variables are higher than 0.8. The second highest correlation is between the market value and the market to book ratio at 0.276. The highest correlation is between the debt/equity ratio and the market to book ratio at -0.683. Therefore, the degree of collinearity present among explanatory variables appears to be too small to degrade the statistical results.

[Insert Table 2 here]

A set of 37 rules was generated by IXL from the training examples corresponding to the discovery parameters specified by the authors. For example, a minimum level of confidence in forming a rule by IXL (specified by the value of “CF” for the rules generated by IXL) was set at 70 percent. Thus, each of the 37 rules generated by IXL had a “CF” value of 70 percent or more. Also, a maximum rule length of 4 clauses, and a minimum applicable number of records of 5 were specified. These values of the discovery parameters were considered to be appropriate for the current investigation by the authors based on their experience with IXL. Rules with multiple clauses in the “IF” part involved only "AND" clauses. Some of the rules with high margins of error and low CF factors were excluded by the authors based on their experience with IXL. Thus, the 37 rules generated by IXL were reduced to a total of 29 rules which were incorporated in the knowledge-base of ACQTARGET.

Consideration of Uncertainty in ACQTARGET

In the real-world applications of expert systems, provision must be made to consider uncertainties involved in decision making. In using an "IF...THEN" rule to draw a conclusion, two sources of uncertainty may be considered. The first source of uncertainty lies with the accuracy of the facts represented by the clauses in the "IF" part of the rule. The second source of uncertainty lies with the accuracy of the rule itself. VP-Expert allows the user of the expert system to deal with both types of uncertainty. For the first type of uncertainty, the user can supply a “CNF” value for each fact in the clauses of the “IF” part of the rule during the expert system consultation process. For the second type of uncertainty, the user can encode a “CNF” value in the “THEN” part of the rule during the creation of the knowledgebase. If the user chooses not to supply any “CNF” value for the “IF” part during consultation, or not to encode any “CNF” value for the “THEN” part during the creation of the knowledgebase, VP-Expert uses a default value of 100 percent for “CNF” in either case.

In this research, the default value of 100 percent was used by VP-Expert for the clauses in the “IF” part of the rules because no specific “CNF” values were required to be supplied by the authors during the consultation process of ACQTARGET. This is because the values of the eight variables for each firm in the database did not seem to involve any uncertainty. However, the uncertainty in the rule itself was accounted for by encoding a "CNF" value for the statement in the "THEN" part of each rule during the creation of the knowledgebase of ACQTARGET in VP-Expert. The value of this “CNF” for a rule entered in VP-Expert was determined by the authors based on the confidence factor "CF" as well as the margin of error calculated and outputted by IXL while generating the rules (see examples of rules generated by IXL presented earlier). The accuracy of the classification made by ACQTARGET for a given case either as an acquisition firm or a non-acquisition firm was computed by the inference engine of VP-Expert based on the “CNF” values of the rules encoded in the knowledgebase.

5. VALIDATION OF ACQTARGET

To test the ability of the expert system to classify firms into acquisition and non-acquisition groups, we examined the predictive ability of ACQTARGET in two different ways: 1) with a holdout sample and 2) with two statistical models, namely, multiple discriminant analysis (MDA) and Logit. O'Leary (1987) suggests that while validating an expert system, objectivity is very important. One way accomplish this would be to use different sets of data for development and testing. We employ a training sample to build the system and a holdout sample to test it. Tables 3 and 4 show the results obtained from the expert system, MDA, and the Logit model applied to the training sample and the holdout sample, respectively.

Tables 3 and 4 show that the expert system can classify firms into acquisition and non- acquisition groups fairly accurately. Panel A of Table 3 gives the training sample results indicating that the expert system classifies 95.4 percent of the acquisition and 80.0 percent of the non- acquisition cases correctly. Panel A of Table 4 shows that when the expert system is used to analyze the holdout sample, 81.3 percent of the acquisition and 65.6 percent of the non- acquisition cases are classified correctly.

[Insert Table 3 here]

O'Leary (1987) recommends validating expert systems against other statistical models, if tests against human experts are expensive and difficult to carry out. In this research, we first use the multiple discriminant analysis model as a content validation tool to evaluate the performance of ACQTARGET. The purpose of MDA is to find the linear combination of the explanatory variables that best discriminates between groups that are partitioned. MDA is often applied to problems where the dependent variable is dichotomous. MDA classifies entries into mutually exclusive groups by maximizing the inter-group to intra-group variance-covariance from a set of predictor variables. Conventional statistical methods such as MDA and Logit attempt to arrive at group separation by simultaneously considering all attributes. On the other hand, methods like IXL, recursive partitioning, and Quinlan's ID3 sequentially classify objects into groups by repeatedly partitioning all attributes (see Srinivasan and Kim, 1988).

Tables 3 and 4 give the classification matrix obtained from MDA. Panel B of Table 3 gives the training sample results indicating that the 8-variable discriminant analysis model classifies 95.4 percent of the acquisition and 64.6 percent of the non-acquisition cases correctly. Panel B of Table 4 shows that when the discriminant model is employed to analyze the holdout sample 81.3 percent of the acquisition and 50.0 percent of the non- acquisition cases are grouped correctly. A comparison of the performance of the ACQTARGET with that of the discriminant model results indicate that the expert system performs equally well. We further analyzed the holdout sample results using the normally distributed Z-test for the equality of proportions (see O'Leary, 1998). The expert system is somewhat superior to the MDA model in identifying non-acquisition cases, but the difference is not statistically significant (Z = 1.271). The expert system and the MDA model both predict 81.3 percent of the acquisition cases correctly.

[Insert Table 4 here]

The discriminant analysis results are described in Tables 3 and 4. The canonical correlation for the discriminant function is 0.524, and the Chi-square statistic is 39.771 suggesting significance at p=0.0001 level. The relation between acquisitions and the factors contained in the model appears to be strong. Separation between acquisition and non- acquisition firms, measured by the distance between the centroids, is also significant at the p=0.01 level. Wilk's lambda, a measure of residual discrimination, is 0.726 and suggests that other factors outside the model may also influence acquisitions. However, to an extent, it is not critical to include every variable that might be significant for the purpose of our study. This is because, the major objective of this work is not necessarily to add to the M&A finance literature on determinants and impacts of different variables. Rather, it is to offer a comparative evaluation of different methodologies available to researchers.

We also performed a Logit analysis using the same data sets for the training and the holdout samples and the results are reported in Tables 3 and 4. The training sample results indicate that the 8-variable Logit model classifies 87.7 percent of the acquisition and 75.4 percent of the non-acquisition cases correctly (see panel C of Table 3). When the logit model is applied to analyze the holdout sample, 65.6 percent of the acquisition and 53.1 percent non-acquisition firms are classified correctly (see panel C of Table 4). The holdout sample results indicate that the expert system is slightly better than the Logit model in predicting acquisition cases and the difference is statistically significant (Z = 1.416) only at the 10 percent level. The difference in performance between the expert system and the Logit model in identifying non-acquisition cases, is not statistically significant (Z = 1.02). We used the normally distributed Z-test for the equality of proportions (O'Leary, 1998). The overall results (i.e. when you consider both the training and holdout samples) suggest that the classification accuracy is 82.9 percent for the expert system, 75.3 percent for the multiple discriminant analysis model, and 74.2 percent for the logit model. This shows that the expert system performs at least as well as the discriminant and the logit models.

6. SUMMARY

In this paper, we have outlined the features of an expert system that evaluates and predicts corporate acquisitions. We have also described the development and testing of a prototype expert system, ACQTARGET, which evaluates corporate acquisitions. Expert systems have been proposed as solutions to business problems in a variety of situations. However, the knowledge acquisition bottleneck has posed considerable difficulties in the development of production rules for the expert system. Rule induction is used as an alternative mechanism to traditional knowledge acquisition techniques. We use real world data relating to acquisition and non-acquisition firms to capture uncertain knowledge through rule induction, using IXL, a machine learning program. IXL-generated confidence factors representing the quality of the induced rules have been incorporated into ACQTARGET. During consultation, the expert system can handle additional uncertainty about the values of the financial variables of a firm by incorporating user-supplied confidence factors. The eight variables used in the database for developing ACQTARGET have theoretical support from prior research.

A set of training examples comprising 65 acquisition and 65 non-acquisition firms is used to generate the rules and a separate holdout sample containing 32 acquisition and 32 non-acquisition firms is used to validate the expert system results. The performance of the expert system is also compared with a conventional discriminant analysis model and a logit model using the same data. By using the same dataset to test out different methodologies we compare their effectiveness and add to the repertoire available to study M&A and other phenomena of interest. The results show that the prototype expert system, ACQTARGET, performs as well as the statistical models and can be a useful evaluation tool to classify firms into acquisition and non-acquisition categories.

TABLE 1
CUT-OFF POINTS FOR DISCRETE RANGE OF VARIABLES

Category	B	D	J	M	C	F	K	H
VeryLow	< 1.0	< 0.0	< 2.0	< 0.0	< 0.02	< 30	< 0	< 0.5
Low	>= 1.0 < 2.0	>= 0.0 < 0.05	>= 2.0 < 4.0	>= 0.0 < 0.2	>= 0.02 < 0.05	30 <= X < 60	>= 0 < 15	>= 0.5 < 0.75
Medium	>= 2.0 < 3.0	>= 0.05 < 0.10	>= 4.0 < 6.0	>= 0.2 < 0.5	>= 0.05 < 0.08	60 <= X < 75	>= 15 < 25	>= 0.75 < 1.0
High	>= 3.0 < 5.0	>= 0.10 < 0.17	>= 6.0 < 10.0	>= 0.5 < 2.0	>= 0.08 < 0.15	>= 75 < 185	>= 25 < 35	>= 1.0 < 1.5
VeryHigh	>= 5.0	>= 0.17	>= 10.0	>= 2.0	>= 0.15	>= 185	>= 35	>= 1.5

Description of the Variables:

B = Current Ratio
C = Capital Expenditure to Total Assets
D = Cash flow to Sales
F = Square root of Market Value
H = Beta
J = Market to Book ratio
K = Price-Earning Ratio
M = Debt/Equity ratio

TABLE 2
PEARSON CORRELATION COEFFICIENTS

	B	C	D	F	H	J	K	M
B	1.000							
C	-0.067 (0.357)	1.000						
D	-0.119 (0.098)	-0.361 (0.000)	1.000					
F	-0.120 (0.096)	-0.037 (0.611)	0.058 (0.419)	1.000				
H	0.205 (0.004)	-0.068 (0.344)	0.026 (0.720)	0.108 (0.135)	1.000			
J	-0.067 (0.353)	-0.024 (0.742)	0.021 (0.770)	0.276 (0.000)	-0.001 (0.991)	1.000		
K	-0.224 (0.002)	0.101 (0.161)	0.001 (0.984)	0.133 (0.065)	-0.259 (0.000)	0.104 (0.150)	1.000	
M	0.000 (0.998)	0.009 0.903)	-0.004 (0.955)	0.043 (0.550)	0.037 (0.612)	-0.683 (0.000)	0.003 (0.968)	1.000

(Significance level is given within parentheses)

Description of the Variables:

B = Current Ratio
C = Capital Expenditure to Total Assets
D = Cash flow to Sales
F = Square root of Market Value
H = Beta
J = Market to Book ratio
K = Price-Earning Ratio
M = Debt/Equity ratio

TABLE 3
TRAINING SAMPLE RESULTS

Panel A: Expert system ACQTARGET

CLASSIFICATION MATRIX		PREDICTED GROUP		TOTAL
ACTUAL GROUP	% CORRECT	ACQ.FIRMS	NON-ACQ.FIRMS	
ACQ. FIRMS	95.4%	62	3	65
NON-ACQ. FIRMS	80.0%	13	52	65

TYPE I ERROR : 4.6% *
TYPE II ERROR : 20.0%

Panel B: MDA

CLASSIFICATION MATRIX		PREDICTED GROUP		TOTAL
ACTUAL GROUP	% CORRECT	ACQ.FIRMS	NON-ACQ.FIRMS	
ACQ. FIRMS	95.4%	62	3	65
NON-ACQ. FIRMS	64.6%	23	42	65

TYPE I ERROR : 4.6% *
TYPE II ERROR : 35.4 %

Panel C: LOGIT

CLASSIFICATION MATRIX		PREDICTED GROUP		TOTAL
ACTUAL GROUP	% CORRECT	ACQ.FIRMS	NON-ACQ.FIRMS	
ACQ. FIRMS	87.7%	57	8	65
NON-ACQ. FIRMS	75.4%	16	49	65

TYPE I ERROR : 12.3% *
TYPE II ERROR : 24.6%

* - Type I (II) error is defined as the percentage of firms that were classified as non-acquisition (acquisition) targets, while they were actually acquisition (non-acquisition) targets.

TABLE 4
HOLDOUT SAMPLE RESULTS

Panel A: Expert System ACQTARGET

CLASSIFICATION MATRIX		PREDICTED GROUP		TOTAL
ACTUAL GROUP	% CORRECT	ACQ.FIRMS	NON-ACQ.FIRMS	
ACQ. FIRMS	81.3%	26	6	32
NON-ACQ. FIRMS	65.6%	11	21	32

TYPE I ERROR : 19.7% *
TYPE II ERROR : 34.4%

Panel B: MDA

CLASSIFICATION MATRIX		PREDICTED GROUP		TOTAL
ACTUAL GROUP	% CORRECT	ACQ.FIRMS	NON-ACQ.FIRMS	
ACQ. FIRMS	81.3%	26	6	32
NON-ACQ FIRMS	50.0%	16	16	32

TYPE I ERROR : 18.7% *
TYPE II ERROR : 50.0%

Panel C: LOGIT

CLASSIFICATION MATRIX		PREDICTED GROUP		TOTAL
ACTUAL GROUP	% CORRECT	ACQ.FIRMS	NON-ACQ.FIRMS	
ACQ. FIRMS	65.6%	21	11	32
NON-ACQ. FIRMS	53.1%	15	17	32

TYPE I ERROR : 34.4% *
TYPE II ERROR : 46.9%

* - Type I (II) error is defined as the percentage of firms that were classified as non-acquisition (acquisition) targets, while they were actually acquisition (non-acquisition) targets.

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