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Classification Problem for Tax Purposes**

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NEURAL NETWORK ANALYSIS OF THE EMPLOYEE

CLASSIFICATION PROBLEM FOR TAX PURPOSES

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ABSTRACT

Since 1987 the U.S. Internal Revenue Service has relied on twenty common law factors for guidance in determining whether a worker is an employee or an independent contractor. This study presents new evidence on the task of simplifying that complex classification problem. Neural network methodology is used to classify workers using data obtained from Private Letter Rulings issued by the Internal Revenue Service from 1988 through a portion of 1993, a data set not previously used for this purpose. The model is highly accurate in correctly classifying workers as either employees or independent contractors. The overall prediction success rate using sample data was 97.2 percent and drops to 91.4 percent when a holdout sample was used. These findings are robust for each of the years in the study. For comparison purposes, classification results using logistic regression are also included. Results from both methodologies are identical.

RESUMEN

Desde 1987 el Servicio de Recaudación Interna de los Estados Unidos ha confiado en veinte factores definidos por ley para guiarse en la clasificación de empleados y trabajadores independientes. Este estudio presenta nueva evidencia para simplificar el complejo problema de dicha clasificación. Mediante el uso de redes neuronales (neural networks), la clasificación se realiza utilizando declaraciones (Private Letter Rulings) del Internal Revenue Service desde 1988, hasta una porción de 1993, un banco de datos no utilizado hasta el momento. El modelo es altamente preciso en la clasificación de trabajadores como empleados o trabajadores independientes. El porcentaje de predicciones correctas es de un 97.2%, y cae al 91.4% para valores fuera de la muestra. Estos resultados son robustos para cada uno de los años incluidos en el estudio. A los efectos de comparación, también se incluyen resultados de la clasificación utilizando regresión logística. Ambas metodologías producen idénticos resultados.

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1 Introduction

Statistical techniques have been used for many years in tax research and have proven useful in minimizing the uncertainty in predicting the outcome in taxation issues. Linear regression, multiple discriminant analysis, logistic regression and probit are examples of procedures that have been used with varying degrees of success. Porcano and Porcano (1985) provide an excellent review of these techniques. However, all of these techniques possess limiting conditions. Conditional relationships are not permitted, distributional assumptions are required and in some cases linearity is imposed. In addition, they are not interactive and frequently consume sizable degrees of freedom. A new technique, neural networks, is an alternative to traditional statistical methods that overcomes most of these restrictive conditions.

Neural networks are highly effective tools for handling predictive and classification tasks. A neural network is basically a simplified model of the human brain which is capable of learning and generalization. As such, neural networks are information processing structures. They constitute computational systems that can be used for a number of applications, including pattern recognition and classification problems.¹ Originally they were designed for the understanding of the learning process in humans. Neural networks simulate the behavior of the nervous systems in the learning process. A neural network can be described through its characteristics. These are: (1) the existence of a structure, (2) the dynamics of the process, and (3) the capability of learning. Simply stated a neural network has the property of analyzing data (input) and through learning, establish a conclusion (output) according to the task to be performed. The purpose of this study is to introduce neural networks as a potentially powerful research tool in taxation and to present an example of its application to the employee classification problem. The remainder of this paper is organized as follows. A neural network model is presented and discussed in Section 2. The background for the employee classification problem is presented in Section 3. The methodology and data are discussed in Section 4. Results are presented in Section 5 and conclusions are provided in Section 6.

2 Neural Network Model

The basic structure of a neural network consists of input processing elements and output processing elements arranged in layers and interconnected through paths, or connecting weights. Additional layers other than input and output are referred to as hidden layers. Neural networks are different from artificial intelligence and from static statistical classification systems (like multiple discriminant analysis) in that the process is dynamic. Neural networks have the ability to adapt to new environments, and learn in the process by illustration and example. As compared with statistical procedures, neural networks are a non-parametric technique, and assumptions on the data are not necessary. One of the most powerful applications of neural networks is in the field of pattern recognition, which is mainly a classification tool. Other applications in business include bond quality assessment (Dutta and Shekhar, 1988), fraud detection (Shandle, 1993), forecasting, credit evaluation (Coats and Fant, 1993), information asymmetry (Eynon and Stevens, 1995), loan underwriting (Collins, et al. 1988), and quality control.

In the context of this paper, neural networks provide a very appealing tool for classification of employees and independent contractors. Inputs are identified as the characteristics or attributes described in the law that allow for the definition of employees, and output refers to the decision made by the IRS. As a result of applying neural networks to a classification problem, weights are computed which represent the strength of the connection, that is, of the association between each input and the corresponding processing element above it. These weights are very important in determining which characteristic is more influential in the classification process. The neural network system created by NeuralWare Inc. (1993) was used in this classification problem.

Neural networks use different types of learning algorithms. In this case, the back-propagation algorithm was used. This is the best known and most common algorithm applied in neural network systems. Its name comes from the way errors are handled. If a classification is wrong (actual and predicted value differ), the method goes back to the different connections and modifies their weights, until an error global function is minimized which is the goal of the learning process. A two-layer neural network has an input layer which can be represented by a vector such that $x = (x_1, x_2, \dots, x_n)$ of characteristics and an output layer which can be represented by an output vector $y =$

$g(x)$. Assuming a single output node $y = g(x)$, the connection weights are represented by β_i , where $i = 0, \dots, n$, and a linear transfer function results. It therefore follows that

$$y = g(x) = \sum \beta_i x_i \quad (1)$$

Therefore, the linear regression model is similar in form to a two-layer neural network which has a linear transfer function. In this two-layer model with a linear transfer function, neurons are not activated until some threshold level y_0 is reached. Therefore,

$$y = F \left[\sum \beta_i x_i \right] \quad (2)$$

where $F = 1$ when $\sum \beta_i x_i > y_0$, and 0 otherwise. Since the function F can be any continuous function, F can represent a cumulative distribution. When F is characterized by a normal cumulative distribution then $F[\sum \beta_i x_i]$ is a conditional expectation variable generated by a probit model. When F is a logistic cumulative distribution frequency then $F[\sum \beta_i x_i]$ is the conditional expectation generated by the logistic function. Thus, a two-layer neural network model will produce identical results to the familiar probit and logit regression techniques depending on the distribution of the underlying data.

In this study, we employ a three-layer, feedforward, backpropagation neural network process. Following White (1989), for a three-layer network, any hidden layer will receive a weighted sum of all the input nodes plus a bias and produces an output signal such that

$$k_j = \tau \left[\sum_{i=0}^n w_{ij} x_i \right] \quad j = 1, \dots, n, \quad (3)$$

here τ is the transfer function, x_i is the i -th input signal, w_{ij} is the strength of the connection from the i -th input node to the j -th middle layer node and k_j is the hidden layer node. The signals from the hidden nodes are sent to the output nodes in a similar fashion to (3) and produces a signal

$$m_k = \tau \left[\sum_{j=0}^s \beta_j k_j \right] \quad (4)$$

where there are s hidden nodes, β_j is an output weight, m_k is the k -th output node, and k_0 is always one so that β_0 provides a bias. By substituting equation (3) into (4)

we have

$$y = \tau \left[\sum_{i=0}^n \beta_j \tau \left(\sum_{i=0}^n w_{ij} x_i \right) \right] = f(x, \theta), \quad (5)$$

where output (y) is shown as a function of the input vectors (x) and weights (θ). White (1989) shows that the output function, $f(x, \theta)$ provides an accurate approximation to almost any function of x provided s (the number of hidden layers) is large enough. Because of this property, hidden-node, feedforward neural networks are very useful in forecasting, classifying, and pattern recognition.

3 Employee Classification Problem

The misclassification of employees and their treatment as independent contractors is both widespread and increasing (Green 1993). The Internal Revenue Service (IRS) estimates that 3.4 million workers are incorrectly classified by one of every seven employers (Murphy 1989). In May, 1989 the General Accounting Office (GAO) reported that at least \$1.6 billion in tax revenues were lost as a result of improper classification of employees. The loss occurred because employers failed to collect and pay employment taxes and independent contractors claimed tax benefits to which they were not entitled (Posner 1989).

As a result of widespread non-compliance with this area of the tax law, the IRS continues to enhance and expand initiatives to increase compliance (Moore and Turk, 1993). Interest in this issue is pervasive because penalties that may be assessed against employers deemed in non-compliance are extensive (Gold and Esposito 1992; Kenny and Hulen 1989; O'Rourke, 1990) and enforcement is becoming more rigorous. The aforementioned issues notwithstanding, section 530 of the Revenue Act of 1978 established a moratorium on the reclassification of workers as employees if the employer had a "reasonable basis" for not treating the workers as employees.

Determining the correct status of a worker is a complex task and the ultimate determination rests with the application of common law principles when statutes are not specific. Every working relationship is unique and therefore necessitates a case-by-case

determination. Generally, a worker is an employee when the employer has the right to control the activity of the worker not only as to the result to be achieved but also as to how, when, and where the work is to be performed (Rev. Rul. 87-41). Furthermore, the ultimate determination is based on the actual conduct of the parties in the relationship rather than the existence of a definitive written contract. The Revenue Service has a demonstrated bias in favor of classifying all workers as employees and no incentive to reclassify employees as independent contractors. For this reason the IRS has targeted employers with total assets less than \$3 million [Murphy (1989), p. 78].

Under Revenue Ruling 87-41, the IRS employs twenty factors (see Appendix I), developed from common law principles, to evaluate when the control exercised by the employer is sufficient to classify the worker as an employee. Several authors (Merritt 1991; Sumutka 1992; Stewart 1982) question the need for this many factors and suggest that fewer factors can be used to make the necessary classifications. Currently, the ultimate determination is based on a subjective application of the common law principles to each case (Church and Lambert 1993). The subjective nature of the process creates uncertainty for every party with a vested interest in the correct classification of workers.

At a June, 1995 meeting of the White House Conference on Small Business, a poll of the business owners serving as delegates was conducted. A recommendation to clarify the definition of an independent contractor received more votes than any other issue. As a result, H.R. 1972 the Independent Contractor Tax Simplification Act of 1995 was introduced in the House of Representatives on June 30, 1995. The Act has the purpose of establishing fair and objective rules for determining who is an employee and who is an independent contractor. The objective of this study is to analyze the results of previous IRS Private Letter Rulings to determine: (1) if a predictive classification model can be developed that is accurate and reliable; and (2) to assess the relative importance of the determining factors. It is anticipated that these results will prove useful for those contemplating an employment structure utilizing workers classified as independent contractors.

In addition, the misclassified employee is liable for taxes that would apply to business expense deductions incorrectly taken. Potential liability is not limited to these two parties; it also extends to accounting firms which attest to the fairness of financial statements, and preparers of tax returns.

3.1 Background

Federal employment taxes are those contained in the Federal Insurance Contributions Act (FICA), the Federal Unemployment Tax Act (FUTA) and the Collection of Income Tax at Source on Wages. Generally, all three charge the IRS with the responsibility for the collection of these taxes. They do not apply when the worker is an independent contractor, but are applicable when the relationship is that of an employer/employee. Guidelines for determining whether a worker is an employee are provided in Treasury Regulations.

Treasury Regulations state that an employer/employee relationship is deemed to exist when the employer has the right to control and direct the worker as to the details and means by which work is to be accomplished (Reg. 31.3121(d)-1(c)(2)). Whether a worker is an employee or an independent contractor under common law rules is a question of fact to be determined by considering and evaluating the circumstances surrounding each individual case.

In his 1982 study, Stewart analyzed 148 District Court and Court of Claims decisions rendered over the period 1940 through 1980. Logistic regression with stepwise entry was used. Five variables entered Stewart's model and are described in Table 1.

In a 1991 lecture presented at the Annual Southern Federal Tax Institute, Merritt describes seven factors that are deemed important in classifying workers as either employees or independent contractors. Merritt goes on to state that these seven can be condensed into two or three factors. Table 1 contains a summary of the seven factors identified by Merritt.

In his 1992 study, Sumutka analyzes the twenty common law factors developed under Revenue Ruling 87-41. The analysis consists of a subjective review of 40 U.S. District Court cases to determine the degree of emphasis placed on each common law factor. He reports finding eight primary factors. These eight factors are also summarized in Table 1.

[INSERT TABLE 1 HERE]

The purpose of the summary presented in Table 1 is to highlight the disparity in opinions concerning the factors important to the employee/independent contractor classification problem. While Table 1 does not present a comprehensive survey of the exten-

sive literature on this topic, it does illustrate widespread diversity of opinion. All three studies agree that the problem can be reduced to fewer than twenty factors. However, there is some difference across these studies as to the number and identity of relevant factors. Common to all three studies are two factors: (1) the degree of supervision by the employer over the worker and (2) whether the worker has an opportunity to earn a profit or sustain a loss. In addition, Merritt identifies two factors that appear in Stewart's model: (1) the extent to which the work is integrated into the normal operations of the employer and (2) the continuity of the working relationship. These latter two variables do not appear in Sumutka's analysis.

The data used by Sumutka (1992) and Stewart (1982) were obtained from courts of original jurisdiction. In both studies a sample selection bias arises because their samples do not represent all courts of original jurisdiction. Stewart appropriately acknowledges this limitation but provides no data to show how serious this potential problem may be.

Since courts rely heavily on precedent decisions there is a chronological ordering to the identification and use of certain explanatory variables. Such reliance is likely to cause a large number of missing observations. For instance, suppose that whether or not the employer reimburses the worker for ordinary expenses is identified in 1960 as a determining characteristic. One would expect each court subsequent to this date to consider this factor in making a decision. Conversely, each case decided before 1960 would not likely discuss this issue, therefore it would be missing. To overcome this problem, Stewart uses a trichotomous coding scheme for his independent variables such that 1 indicates missing, 2 indicates that the factor is considered and found negative, and 3 indicates that the factor is considered and found positive. This coding scheme controls adequately for missing observations but, in so doing, renders coefficients that cannot be interpreted in any meaningful way. Since a principal objective of this study is to extend the analysis of Stewart's seminal work by evaluating the relative importance of the explanatory variables, a different source of data is necessary to avoid both potential sample selection bias and frequent missing observations. Generally, we follow Stewart's methodology so that our results will be comparable.

4 Methodology and data analysis

4.1 Data

Either an employer or a worker may seek a Private Letter Ruling from the National Office of the IRS to determine the classification of the worker for FICA, FUTA and income tax withholding purposes. Private Letter Rulings are issued to the requesting party and other individuals affected by the ruling. These rulings do not set precedent and may be used only by the parties to whom they are addressed. While these published rulings have limited usefulness, they do contain a recitation of the facts on which the ruling relies, a discussion of the applicable law and regulations, as well as the factors and reasoning used in reaching the final determination. The ruling results in a determination of whether the subject worker is an employee or independent contractor. This is essentially a two-way classification process that lends itself to techniques that are either statistical or non-statistical. Statistical techniques would include factor analysis, discriminant analysis, cluster analysis, or probabilistic methods such as logistic regression. Non-statistical methods would include ad hoc subjective methodologies, or newer techniques such as neural network systems. Neural networks offer certain advantages which make them attractive for the task at hand.

The basic structure of a neural network consists of input processing elements and output processing elements arranged in layers and interconnected through paths, or connecting weights. Additional layers other than input and output are referred to as hidden layers.

Neural networks are different from artificial intelligence and from static statistical classification systems (like multiple discriminant analysis), in that the process is dynamic. Neural networks have the ability to adapt to new environments, and learn in the process by illustration and example. As compared with statistical procedures, neural networks are a nonparametric technique, and assumptions on the data are not necessary. One of the most powerful applications of neural networks is in the field of pattern recognition, which is mainly a classification tool. Other applications in business include forecasting, credit evaluation, and quality control, among others.

In the context of the problem of this paper, neural networks provide a very appealing tool for classification of employees and independent contractors. Inputs are identified

as the characteristics or attributes described in the law that allow for the definition of employees, and output refers to the decision made by the IRS. As a result of applying neural networks to a classification problem, weights are computed which represent the strength of the connection, that is, of the association between each input and the corresponding processing element above it. These weights are very important to determine which characteristic is more important in the classification process. The neural network system created by NeuralWare Inc. (1993) was used in this classification problem.

Neural networks use different types of learning algorithms. In this case, the back-propagation algorithm was used. This is the best known and most common algorithm applied in neural networks systems. Its name comes from the way errors are handled. If a classification is wrong (actual and predicted value differ), the method works goes back to the different connections and modifies their weights, until an error global function is minimized which is the goal of the learning process.

4.2 Data and Preliminary Analysis

Private Letter Rulings issued from 1988 through the forty-third week of 1993 were used for this study. The source for the letter rulings was the IRS Letter Rulings Reporter microfiche edition. Each letter ruling issued during this period was read and analyzed. From this analysis the presence or absence of twenty factors (see Appendix I) was determined for each of the available cases. The sample consists of 525 observations which represents over ninety percent of the population of letter rulings issued during the period. A portion of the sample consisting of 35 observations is held out for model validation purposes. Of the cases selected, twenty-two contain insufficient data due to missing values or variables that were indeterminable from the analysis necessitating their omission. A value was missing if the letter ruling did not discuss the factor in question. A factor was indeterminable if the parties involved in the case were in disagreement as to the nature of the working relationship and the IRS provided no guidance as to which party it believed.

Of the remaining 468 cases, 424 resulted in classifying the worker as an employee, and 44 (9.4% high frequency of employee classifications indicates skewness in the dependent variable. However, since the sample represents such a large portion of the population no

sample selection bias results. This fact notwithstanding, the proportion in the sample is very close to the proportion of self-employed individuals in the U.S. population.

In 465 of the 468 cases, the employer initiated the request for a ruling in 25 percent of the cases and the worker initiated the request in 75 percent. This is consistent with the idea that many of the requests were initiated by workers who felt that they were incorrectly classified.

In 410 cases, a determination of the classification status of the worker prior to the request for a ruling was ascertainable. Prior to the request for a ruling, five percent were classed as employees and 95 percent as independent contractors. After the IRS ruling, 90 percent were classified as employees and 10 percent were classed as independent contractors. This indicates that a substantial number of the letter rulings resulted in a change in the classification of the worker.

[INSERT TABLE 2 HERE]

The distribution of the sample is heavily concentrated in the years 1988 and 1989 which contain 88 percent of the observations. This is not surprising since the formal procedure for obtaining a ruling was announced in 1987. To some extent, this concentration can be categorized as pent-up demand for clarification of employment status. It is also likely that many requests were made by individuals who felt that they were misclassified and sufficiently disgruntled to take corrective steps (Frank 1989). However, this does not bias the sample for two reasons: (1) the motivation for requesting a determination letter does not influence the outcome inasmuch as both parties have an opportunity for input, and (2) the sample represents a large proportion of the total population of letter rulings issued over the period studied.

5 Results

5.1 Neural Network Analysis

A model using all twenty of the explanatory variables was estimated. From the weights obtained, the six variables with the highest absolute weights are selected for further

analysis. New models are iteratively estimated, eliminating at each iteration the variable with the lowest weight. The results of this iterative estimation process are presented in Table 3.

[INSERT TABLE 3 HERE]

The six variables with the highest weights are presented in the last column of Table 3. These variables are: (1) does the employer set the hours of work, (2) is the worker required to render reports, (3) are the workers expenses reimbursed by the employer, (4) does the employer provide tools and materials, (5) is the worker shielded from earning a profit or sustaining a loss, and (6) does the worker make services available to the general public? The least influential of these six variables is whether the workers expenses are reimbursed. This variable is eliminated and the weights estimated using the remaining five independent variables. The single variable that survives this process is whether the employer provides tools and materials, suggesting that this factor is very important in determining the classification of a worker.

[INSERT TABLE 4 HERE]

The predictive accuracy of each of the potential models is presented in Table 4 using within-sample data as well as a holdout sample. The cutoff point for making the classification decision is a score of .3. Predicted values for the outcome variable greater than .3 are classed as employees and predicted values equal to or less than .3 are classed as independent contractors. Using within-sample data to test the models, the one variable model correctly predicts the classification of 100 percent of the employees but zero percent of the independent contractors. The overall accuracy is 90.7 percent. The two variable model is more accurate, correctly predicting 99.1 percent of the employees and 77.8 percent of independent contractors for an overall accuracy of 97.2 percent. Further improvement in accuracy is not achieved until five variables are included and, even then, the marginal improvement is minimal. Similar results are obtained using the holdout sample. The best fitting model is the two variable model with an overall accuracy percentage of 91.4. The two variables are whether the employer supplies tools and materials and whether the worker is shielded from a profit or loss.

5.2 Logistic regression

For comparative purposes the previous analysis using neural network methodology was repeated using logistic regression, a well known parametric procedure [see Hosmer and Lemeshow (1989)]. The logistic model was approximated using a stepwise procedure (similar to forward entry). Under the stepwise procedure used, entry into the model required that the estimated coefficient be significant at the .05 level. The five most influential independent variables identified with the neural network procedure also enter with the logistic regression stepwise entry procedure.

The logistic regression model predicts the probability that a worker will be classified as an employee. However, since the prediction is a number between zero and one, there is a need to determine which values of the estimated probability will be considered "close to one" and which values "close to zero" so a predicted classification can be determined. The higher the cutoff point the higher the probability of making a mistake by classifying an individual as independent contractor. At the same time, the probability of misclassifying an employee varies inversely with the cutoff point. Since the former is the probability that we want to minimize, results are presented using a cutoff point of $P=0.3$, which implies that an individual will be classified as an employee if the predicted probability is greater than 0.3. Otherwise, the individual is classified as an independent contractor.

Five of a possible twenty variables entered both our models and were the same for both procedures. The five variables are: (1) Does the employer set the working hours? (2) Does the employer provide tools and materials? (3) Is the worker shielded from a profit or a loss? (4) Does the worker make services available to the general public? and, (5) Does the employer require written or oral reports.

Maximum likelihood estimates of the logit model are presented in Appendix II. The value of the likelihood ratio test (233.2) for joint significance of explanatory variables (similar to an F-test) allows the rejection of the null of no relationship. Using a two-tailed t-test, all the coefficients in the logistic regression are significantly different from zero with high confidence levels. In addition, the odds ratio for each of the five variables was derived and is presented in Appendix II.

The model was validated using a holdout sample consisting of the last 35 cases drawn from the year 1993. Table 5 presents a summary of the forecast performance using both

within-sample as well as holdout sample data.

[INSERT TABLE 5 HERE]

It is apparent that the predictive power of the logistic model, using five variables, was virtually identical to the results achieved with the neural networks methodology. The best model employs only two variables and has an overall success rate of 91.4 percent for out-of-sample data.

For practical purposes, one can determine which variable is the most important factor, and second, estimate the marginal contribution in probabilistic terms of being classified as employee once a given variable has been answered as "yes." This is done by computing the change in the probability of being classified as employee conditional on a given answer. Appendix III presents the predicted logit value, the predicted probabilities and the marginal contribution of each variable answered "yes" to the probability of being classified as employee. These probabilities were computed assuming a variable was answered first, and then adding one variable at a time to determine the probability of being classified as employee as each variable was added. For the 120 combinations possible ($n!=5!$) Appendix III presents the results for which the probability of being classified as employee is the highest once three questions have been answered in the affirmative. The only singular factor indicating classification as employee was when the worker has no opportunity to earn a profit or sustain a loss. If the worker has no opportunity to earn a profit or sustain a loss, then the marginal probability of .61 assures classification as an employee. This indicates that the inability of a worker to earn a profit or sustain a loss is a condition sufficient, but not necessary, for classification as employee and no additional information is necessary. However, the worker's capacity to earn a profit or sustain a loss does not necessarily imply classification as an independent contractor. If the worker can earn a profit or loss, then classification as an employee will still ensue if the employer requires written or oral reports and sets the hours of work. Stated differently, if the worker has no opportunity to earn a profit or loss, then the worker must be classed as an employee. If the worker has an opportunity to earn a profit or sustain a loss, then classification as an independent contractor may ensue provided the employer exercises little or no control over the worker.

5.3 Potential Limiting Conditions

From the various tests we have used, it is clear that the logit model is very successful in predicting the outcome of an IRS determination using only five variables. However, in evaluating the relative importance of each of these variables there remains some possibility that one of the included variables is serving as a proxy for some omitted explanatory variable. Our test of the fifteen variables excluded from the model indicates that no information is lost. Nonetheless, there remains some possibility that any of the variables in the model and their relative importance could be representing some other unidentified explanatory factor. Interpretation and use of these findings should be tempered with the realization of this possibility.

6 Concluding Remarks

The incorrect classification of workers for income tax purposes is costly to employers and workers. Employers are exposed to potential liability for taxes not withheld, penalties for failing to withhold, and claims by workers for lost fringe benefits. Workers are potentially liable for deductions taken for which they were not eligible.

The question of assessing a particular working relationship to determine the correct status has been addressed in this study. The evidence indicates that three variables are highly indicative of whether the working relationship is one of employee or independent contractor. If the worker is shielded from earning a profit or sustaining a loss, then the worker is classified as an employee. If the worker can earn a profit or take a loss, then classification as an employee can still arise if the employer sets the hours of work and requires either written or oral reports. The predictive accuracy of the model using only these factors is high. When tested on the sample used to estimate the parameters the overall success rate is 98.5 percent and when tested using a holdout sample, the overall success rate drops to 91.4 percent.

Interest in this topic extends beyond the employer and the worker. Both tax attorneys and accountants have a vested interest in the correct classification of workers because they are frequently consulted for professional assistance in structuring independent contractor agreements. In addition, auditors are frequently held accountable for

undisclosed liabilities under their attestation function. Use of the model developed in this study will assist all interested parties in removing some of the uncertainty in the employee classification process.

From a public policy perspective substantial revenues are lost as a consequence of non-compliance which in turn forces substantial public resources to be devoted to enforcing compliance. Therefore, considerable social cost occurs from the incorrect classification of workers as independent contractors. Such high costs could be reduced if the criteria for determining the status for independent contractors was made less complex.

The factors identified in the model are easily determined and the decision rule is considerably less complex than the criteria currently in use. The adoption of such a simple model would still provide satisfactory classification results while removing the high level of uncertainty that currently surrounds the vague statutory definition of common law employees.

Appendix I

TWENTY COMMON LAW FACTORS FOR DETERMINING EMPLOYMENT STATUS UNDER REVENUE RULING 87-41

1. Instructions. If the employer gives instructions to the worker concerning how, when, and where the work is to be performed, then the employer is exercising control indicative of an employer/employee relationship. It is sufficient if the employer has the right to give instructions and does not require that instructions actually be given. [Revenue Ruling 68-598, CB 464 and Revenue Ruling 66-381, CB 449].
2. Training. If the employer provides training to the worker, then the employer is exercising control as to how the work is to be performed. Training can take the form of compulsory attendance at meetings, seminars, sales meetings, etc. It is also present if the worker is required to perform services in the company of an employee. [Revenue Ruling 70-630, CB 167].
3. Integration. If the services provided by the worker are integrated into the services provided by the employer, then the employer is exercising direction and control. When the economic success of the employer is dependent upon the successful delivery of services and the worker provides these services then integration is present and the employer has a vested interest in how the services are provided. [United States v Silk, 331 U.S. 704(1947), 1947-2 CB 167].
4. Personal Rendering of Service. If the worker must provide services personally, then the employer is presumed to have an interest in the methods used to deliver the service. [Revenue Ruling 55-695, 1955-2 CB 410].
5. Hiring, Supervising, and Paying Assistants. If the employer hires, supervises and pays assistants who help the worker, then an employer/employee relationship is deemed to exist. On the other hand, if assistants are hired, supervised and paid by the worker, then an independent contractor relationship is implied. [Revenue Ruling 63-115, 1963-1 CB 178 and Revenue Ruling 55-593, 1955-2 CB 610].
6. Continuity. If the relationship between the employer and worker is a continuous one or where the relationship is frequently recurring but irregular, then an employer/employee relationship is deemed to exist. [United States v Silk, 331 U.S. 704 (1947)].
7. Hours of Work. If the employer sets the hours of work, then control by the employer is indicated. [Revenue Ruling 73-591, 1973-2 CB 337].
8. Full Time. If the worker devotes full time to the employer such that no opportunity exists for the provision of services to others or the general public, then control over the

worker is indicated such that an employer/employee relationship exists. On the other hand, an independent contractor is free to work for whom he wishes when he wishes. [Revenue Ruling 56-694, 1956-2 CB 694].

9. Where Work Conducted. If the work must be accomplished on the employer's premises, then an employer/employee relationship is indicated because implicit control over how the work is performed is possible. This is especially true if the work could be just as easily accomplished at some other location. [Revenue Ruling 56-660, 1956-2 CB 693]. Furthermore, this manner of control is deemed to exist when the work is accomplished off the employer premises but the employer has the right to designate a route, specific places where the work is to be performed, or to canvass a territory within a specific time period. [Revenue Ruling 56-694, 1956-2 CB 694].

10. Sequence of Work. If the employer has the right to set the order in which the services are to be provided, then control is indicated and an employer/employee relationship would likely exist. On the other hand, if the worker is free to perform services in any order or sequence desired, then independent contractor status is indicated. [Revenue Ruling 56-694, 1956-2 CB 694].

11. Reports. If the employer has the right to require the worker to submit written or oral reports, then control over how and when the work is performed is deemed to be exercised and would be indicative of an employer/employee relationship. [Revenue Ruling 70-309, 1970-1 CB 199, and Revenue Ruling 68-248, 1968-1 CB 431].

12. Mode of Payment. Payment by the hour, week or month is generally indicative of an employer/employee relationship provided that these modes are not just a convenient way of distributing a lump sum contract payment under a progress payment arrangement. Payment made by the job or on a commission basis are indicative of independent contractor status. [Revenue Ruling 74-389, 1974-2 CB 330].

13. Expense Reimbursement. If the employer ordinarily pays the worker's business and travel expenses, then the worker would ordinarily be an employee. This arises because an employer is interested in controlling expenses and therefore is deemed to exercise some control over the incurring of these expenditures. [Revenue Ruling 55-144, 1955-1 CB 483].

14. Tools and Materials. If the employer provides significant tools and materials, then an employer/employee relationship is indicated. This arises because the provision of tools and materials substantially reduces the possibility of the worker incurring either a profit or a loss. [Revenue Ruling 71-524, 1971-2 CB 346].

15. Significant Investment. Lack of an investment in facilities and equipment on the part of the worker tends to be indicative of an employer/employee relationship particularly when a significant investment is required for the performance of services. On the other hand, if a worker provides facilities and equipment, then an independent contractor relationship is indicated. [Revenue Ruling 71-524, 1971-2 CB 346].

16. Realization of Profit or Loss. If a worker is exposed to the potential for profit and or loss, in amounts above that which would occur for an employee providing the same service, then status of an independent contractor is indicated. [Revenue Ruling 70-309, 1970-1 CB 199].

17. Multiple Employers. If the worker provides more than *de minimis* but similar services for a multiple of unrelated employers at the same time, then status as an independent contractor is indicated. However, where a worker provides services to more than one employer the worker may be an employee of each of the employers, particularly if the services are part of the same service arrangement. [Revenue Ruling 70-572, 1970-2 CB 221].

18. Services Available to General Public. If a worker makes services available to the general public on a regular and consistent basis, then status as an independent contractor is indicated. [Revenue Ruling 56-660, 1956-2 CB 693].

19. Right to Discharge. If the employer retains the right to discharge the worker, then an employer/employee relationship is indicated. On the other hand, if the employer cannot discharge the worker as long as the services are in conformity with the specifications of the contract, then status as an independent contractor is indicated. [Revenue Ruling 75-41, 1975-1 CB 323].

20. Right to Terminate. If the worker has the right to terminate the provision of services at will and without incurring liability, then the status of an employer/employee relationship is indicated. [Revenue Ruling 70-309, 1970-1 CB 199].

Appendix II

Logistic Regression Parameter Estimates			
Variable***	Estimate	Standard Deviation	Odds Ratio
INTERCEPT	-4.7149**	0.9656	0.009
X7	2.8554*	1.1996	17.381
X18	2.6706**	0.8532	14.449
X11	2.7763**	0.8699	16.059
X16	2.9062**	0.7801	18.287
X14	1.9488**	0.7623	7.020
-2 LOG L	233.2		
N	468		

*Significant at the 2% level and ** at the 1% level. ***Variables: X7 = Does the employer set the working hours; X11= Does the employer require written or oral reports; X14= Does the employer provide tools and materials; X16= Is the worker shielded from a profit or loss; X18= The worker makes no services available to the general public.

Appendix III

Conditional Probability Estimates							
X7	X11	X14	X16	X18	Logit	Probability	Marginal Probability
0	0	0	0	0	-4.71	0.009	-
1	0	0	0	0	-1.86	0.135	0.126
1	0	0	1	0	1.05	0.74	0.61
1	1	0	1	0	3.82	0.978	0.24
1	1	1	1	0	5.77	0.997	0.018
1	1	1	1	1	8.44	0.999	0.002

0 = negative response and 1 = affirmative response. Variables: X7= Does the employer set the working hours? X11= Does the employer require written or oral reports? X14= Does the employer provide tools and materials? X16= Is the worker shielded from a profit or loss? X18= The worker makes no services available to the general public.

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Table 1
Summary of Factors
Considered Important in Prior Studies*

Factor	Merritt	Sumutka	Hulen et al.	Stewart
1. Supervision by employer	X	X		X
2. Employer provides work facilities	X	X	X	
3. Worker's opportunity for profit/loss	X	X	X	
4. Employer right to discharge worker	X			X
5. Integration	X			X
6. Continuity	X			X
7. Intent of parties	X			
8. Employer sets working hours		X		
9. Employer controls sequence of work		X		X ¹
10. Employer hires, trains assistants		X		
11. Employer provides tools, materials		X		
12. Worker is in independent trade			X	X

*These studies are Merritt (1991), Sumutka (1992), Hulen, et al. (1993), and Stewart (1982). ¹This variable was combined with supervision in Stewart's (1982) study.

Table 2
Frequency Distribution
by Year of Ruling

Year	Count	Percent	Classed as Employee	Percent
1988	187	40.0	167	89.3
1989	225	48.1	207	92.0
1990	34	7.3	31	91.2
1991	6	1.3	5	83.3
1992	13	2.8	11	84.6
1993	3	0.6	3	100.0
TOTAL	468	100.0	424	90.6

Table 3
Neural Network Weights

Variable*	Models					
	Six Variables	Five Variables	Four Variables	Three Variables	Two Variables	One Variables
X7	-2.14	2.02	2.14	-2.27		
X11	1.93	1.97	-1.95			
X13	-1.14					
X14	-3.62	-1.55	-3.19	2.80	2.17	-2.16
X16	-1.41	-2.65	2.41	2.17	-1.83	
X18	1.82	-1.77				

*Variables: X7 = does employer set hours of work; X11 = is worker required to render reports; X13 = are worker expenses reimbursed; X14 = does employer provide tools and materials; X16 = is worker shielded from a profit or loss; X18 = does worker make services available to general public.

Table 4
Summary of Neural Network Classification Results

Panel A: Within-Sample Data (n=388)					
Models	Classification Counts		Misclassification Counts		Percent Correct
	Employee	I.C.**	Employee	I.C.**	
Model 20	351	32	1	4	98.7
Model 6	351	32	1	4	98.7
Model 5	351	32	1	4	98.7
Model 4	350	27	2	9	97.2
Model 3	350	27	2	9	97.2
Model 2	349	28	3	8	97.2
Model 1	352	0	0	3	690.7
Panel B: Holdout-Sample Data (n=35)					
Model 20	25	5	0	5	85.7
Model 6	24	4	1	6	80.0
Model 5	24	5	1	5	82.8
Model 4	24	7	1	3	88.6
Model 3	24	7	1	3	88.6
Model 2	24	8	1	2	91.4
Model 1	25	0	0	10	71.4

*Model 20 = all independent variables*** (X1-X20); Model 6 = variables X7, X11, X13, X14, X16, X18; Model 5 = variables X7, X11, X14, X16, X18; Model 4 = variables X7, X11, X14, X16; Model 3 = variables X7, X14, X16; Model 2 = variables X14, X16; Model 1 = X14. **I.C. = independent contractor. ***Variables: X1=does employer give instructions; X2=does employer provide training; X3=are worker services integrated with employer; X4=must worker provide services personally; X5=does employer hire and pay assistants; X6=is the working relationship continuous; X7=does employer set hours of work; X8=does worker devote full time to employer; X9=is work conducted on employer premises; X10=does employer set the sequence of work; X11=is worker required to render reports; X12=is the mode of payment regular; X13=are worker expenses reimbursed; X14=does employer provide tools and materials; X15=does worker have a significant investment; X16=is worker shielded from a profit or loss; X17=does worker provide services to multiple employers; X18=does worker make services available to general public; X19=does employer have right to discharge; X20=does worker have the right to terminate at will?

Table 5					
Summary of Logistic Regression Classification Results					
Panel A: Within-Sample Data (n=388)					
Models	Classification Counts		Misclassification Counts		Percent Correct
	Employee	I.C.**	Employee	I.C.**	
Model 5	351	31	1	5	98.5
Model 4	349	27	3	9	96.9
Model 3	350	27	2	9	97.2
Model 2	349	28	3	8	97.2
Model 1	352	0	0	36	90.7
Panel B: Holdout-Sample Data (n=35)					
Model 5	24	7	1	3	88.6
Model 4	24	7	1	3	88.6
Model 3	24	7	1	3	88.6
Model 2	24	8	1	2	91.4
Model 1	25	0	0	10	71.4

*Model 5 = variables*** X7, X11, X14, X16, X18; Model 4 = variables X7, X11, X14, X16; Model 3 = variables X7, X14, X16; Model 2 = variables X14, X16; Model 1 = X14. **I.C. = independent contractor. ***Variables: X7=does employer set hours of work? X11=is worker required to render reports? X14=does employer provide tools and materials? X16=is worker shielded from a profit or loss? X18=the worker makes no services available to general public.