Neural Network Analysis of Performance of Sino-Hong Kong Joint Ventures

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Abstract

An artificial neural network model is used to predict the performance of Sino-Hong Kong joint ventures. Performance of international joint ventures remains a relatively under-researched area, yet its importance is well recognized due to the tremendous surge in joint venture activities in the past decade. Data on 1,463 Sino-Hong Kong joint ventures was gathered, allowing for empirical analysis using neural networks and traditional approaches such as logistic regression. The results show that neural networks are indeed a viable approach to modeling the performance of joint ventures. This study identifies and examines the effects of key parameters in neural networks for such modeling efforts. Moreover, in comparison to logistic regression, neural networks provided better results in classification. This paper also attempts to provide a basis upon which neural networks can be used for the purpose of variable selection in statistical modeling.

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1 Introduction

It has been argued that for multinationals to venture into other countries, the returns must be high enough to compensate for the additional costs incurred in dealing with their new environment. At the same time, these venturing firms should also possess specific advantages for them to invest abroad rather than at home. Particularly in the case of Hong Kong, investors will be likely to take advantages of the abundance of low-cost labor, land and materials in China. The tremendous surge of joint venture activities in China, particularly in the past five years, allows the opportunity for such investigation. This paper employs artificial neural networks to model the factors affecting the performance of Hong Kong joint ventures in China. It constitutes the first large scale economic analysis of performance in this area. Researchers are constantly seeking better ways to model the economic determinants of performance. In this paper, we employ artificial neural networks to model the relationship between performance and economic factors and empirically compare the outcome of a neural network model with one using logistic regression. Comparisons will be made in terms of their ability to identify significant factors and overall prediction of performance. The next section provides the rationale for studying the performance of Sino-Hong Kong joint ventures and a description of the data used in this study. Section 3 introduces neural networks and specifically describes neural networks for classification problems. Results of such empirical application are in Section 4, and conclusions are in Section 5.

2 International Joint Ventures

Formation of international joint ventures creates corporate synergism. Local partners, particularly from developing countries, would benefit from the technological know-how, management skills, and capitals brought in by their foreign partners. Multinationals can benefit from their local partners' knowledge of the marketplace and position in the existing distribution network. Economies of scale can be achieved through trust and cooperation among the partners [Contractor and Lorange 1988]. While improving efficiency through combining resources, joint ventures have also created management problems through different goals, values and cultures. Existing literature on joint venture performance indicates the success rate of international joint ventures has been dismal, ranging from 30% to 70% [Geringer and Hebert 1991]. Prior studies focused their attention on the performance of joint ventures in developed countries. As more joint ventures are formed in developing countries, it is important to investigate the performance of these ventures.

In the past decade, foreign investments in China have increased significantly. Previous studies rely on interviews and surveys, securing information from foreign investors on whether or not they are satisfied with their operations in China [Davidson 1987, Shenkar and Zeira 1992, Teagarden and Von Glinon 1990, US-China Business Council 1990]. After successfully gathering a large-sample data set from reliable sources, we fill the void in the literature by conducting the first large scale econometric study on the performance of Sino-foreign joint ventures. Multinationals extend substantial resources in the formation and implementation of these ventures. The profit potentials are huge. They have an obvious interest in accurately predicting the success of these ventures. Even a moderate improvement in model prediction will be of importance to these investors.

2.1 Joint Venture Performance

The literature has identified at least six major categories of factors influencing the performance of a joint venture. Killing [1983] suggests that the level of commitment each party brings to a joint venture to be one of the key determinants of performance. A lack of commitment will lead to an ill-defined set of objectives and lack of overall direction for the organization. Beamish and Banks [1987] based on a sample of 66 joint ventures in the Caribbean economies provide some empirical evidence in support of the positive effect of commitment on performance.

Secondly, joint venture performance is also determined by the amount of control exercised by the foreign partner. After reviewing the relationship between control and performance of a joint venture, Geringer and Hebert [1989] develop a conceptual framework detailing the various components of control and how each may in term affect performance. Ownership constitutes a key control mechanism. Beamish and Banks [1987] report that among twelve international joint ventures formed in less developed countries, performance is negatively related to the level of control exercised by the foreign partner.

Closely related to the concept of control is the problem of shared management. This problem is heightened when the number of partners to a joint venture increases. It is already difficult to serve under two masters let alone when more than two parents are managing the venture. Yet this problem in shared management has to be tempered with the benefits that are gained through coordination and cooperation [Gomes-Casseres 1989]. The benefits of corporate synergism outweigh the costs when the number of partners is small. Yet as the number of partners increases, the problem of shared management may exceed the benefits derived from cooperation. Thus there should be a curvilinear relationship between number of partners and performance.

Performance of international joint ventures is found to be related to the characteristics of the products involved in the ventures. Kogut [1989] studies the stability of 92 US-foreign joint ventures in the United States. Stability is measured in terms of the likelihood of termination. It is found that high technology products due to product differentiation command a stronger market position in the local or foreign markets. These factors allow firms to charge a higher price and engage in nonprice competition. Thus a positive relationship is expected between technological characteristics of a product and performance. Lecraw [1983] examines the performance of 153 joint ventures in Thailand, Malaysia, Singapore, Indonesia and the Philippines and concludes that labor intensive products can easily take full advantage of the abundance of low cost labor in these developing countries. A positive relationship should persist between performance and labor intensity.

Lastly, in a developing country like China, the major business centers are better equipped to conduct business operations. In addition, the Chinese government has also established special economic and technological development and trade zones to foster the development of these activities. In these areas, the tax rates are low and facilities are plentiful. It is envisioned that joint ventures should benefit from the better infrastructure and favorable tax structure. Thus it is proposed that the performance of joint ventures should vary by their business location within the different regions in China.

2.2 Sino-Hong Kong Joint Ventures

Country of origin of foreign investment has been found to be useful in explaining performance. This study focuses on the performance of joint ventures formed by Hong Kong investors in China. While most previous studies use multiple host countries because of small number of foreign ventures in any one host country, by limiting the scope of our study to one host and home country, we eliminate the variations between countries from these two sources. In addition, since Hong Kong investors account for roughly 60% of foreign investment projects in China, limiting the scope of our study to Hong Kong will cause little loss of generality.

2.3 The Data

The data for this study come from two sources: (1) Statement of Sino-Foreign Joint Ventures, 1979-1990 in Almanac of China's Foreign Economic Relations and Trade and (2) Sino-foreign joint ventures honored for their outstanding performance by the China Association of Enterprises with Foreign Investment, a nonprofit organization for Sino-foreign joint ventures. The Statement contains a description of 3,071 Sino-foreign joint ventures, providing names of the ventures, their parent companies' names, geographic location in China, number of years the venture is to exist, amount of total investment, percent of foreign investment, and the primary scope of the business.

Of the 3,071 joint ventures, 2,416 fall in the manufacturing category. In 1989 and 1990, the China Association of Enterprises with Foreign Investment evaluated operating joint ventures and selected 1,187 outstanding manufacturing enterprises. To be included in the Honor Roll, a joint venture must (1) produce high quality products; (2) have a before tax profit exceeding one million yuans; and (3) export value greater than two million US dollars. This study uses those commended on the Honor Roll as successful joint ventures because they must simultaneously produce high quality goods, profits, and export revenue. Profits understandably are important for a foreign joint venture. This measure was adopted by various researchers [Lecraw 1983]. Producing high quality products for exporting is also beneficial to all parties involved. For foreign partners, it is an indication that products produced in China are of good quality and competitive in international markets. Matching the 2,416 joint ventures in the Statement and the 1,187 in the Honor Roll results in 220 joint ventures which received commendation in 1989 or 1990. Of the 2,416 ventures, 1,463 (60.6%) are with Hong Kong investors and of these, 140 are on the Honor Roll. The average investment of these ventures amounts to US$2.442 million, which is relatively small compared to the average of US$3.087 for all Sino-foreign ventures.

2.4 Variables

The dependent variable, performance of joint venture, is coded as 1 for "successful", those listed on the Honor Roll, and 0 otherwise. Independent variables used in this study include level of commitment, foreign control, number of partners, country of origin, industrial characteristics of joint venture products, and joint venture location in China. The level of commitment involved is measured using duration (number of years as specified in the joint venture contract), and total amount of investment. The natural logarithmic transformation is applied to these two variables and the number of partners, yielding LDUR, LINVEST, and LPARTNER. Percent foreign ownership (PFINVEST) is used as a proxy of the level of a foreign investor's control. A larger share of equity ownership would give a partner greater control of a joint venture.

In order to examine the industry related effects, the 2,416 manufacturing joint ventures are classified into high or low technology (TECH), and labor or capital intensive (CAP). This classification scheme was developed by Dunning [1979] and later used by Lee [1983]. A 1, -1 coding is used for each of the two industry related factors (TECH, CAP). TECH is coded as "1" ("-1") for high (low) technology, and CAP as "1" ("-1") for labor (capital) intensive. Economic risk due to differences in joint venture location is examined at the regional level (LOC). There are three regions for LOC. The first are areas with both economic and tax incentives. Corporate income tax rate for joint venture in China is 30%. A local surtax of 10% of this income tax is levied by the local government, thus bringing the effective tax rate to a total of 33%. In the Special Economic Zones and the Economic and Technology Development Zones in the 14 cities, this tax rate is reduced to 15% for foreign investors. LOC = 1 when a venture is in either special zone. The second are areas with economic but no tax incentives.

The coastal regions in China are more economically developed, providing facilities for conducting business operations. A venture in a coastal area outside of the special zones has LOC = 2. The third region (LOC=3) consists of inland provinces, typically lagging in economic development and offering no tax and economic incentives. LOC is coded using two dummy variables, LO1and LO2, with (1, 0) denoting LOC =1, (0,1) for LOC = 2, and (-1, -1) for LOC = 3.

Given that the dependent variable in this study is categorical in nature, either successful or not successful, the problem evolves into one of classification. That is to say, the economic factors will be first used to predict whether a joint venture belongs to one or the other category, and then the resulting functional relationship will be used to classify the observations into one of the two categories. The next section presents a brief review on neural networks and its application to classification problems.

3 Neural Networks For Classification

The neural networks employed in this study are feed-forward networks with one hidden layer. The number of input nodes is equal to the number of variables in the data set. There is one output node, which contains a bias. The activation function at the output and hidden nodes is logistic. A special feature is that the input nodes are connected to not only the hidden nodes but the output node also. The reason for this is to make it as close to logistic regression as possible.

Let x_i be the vector of economic factors of joint venture i. The "target" value is $t_i = 1$ if the venture is successful and $t_i = 0$ if it is not. For a given network, let a_i be the output (there is only one output node) when x_i is the input. Training is accomplished with the following objective function:

$$\min \sum_i (a_i - t_i)^2$$

The quantity to be minimized is called the "sum of squared errors" (SSE). According to the theory of least square estimation (see Hung, *et al.* [1996] for references), the network output a_i is an unbiased estimate of the posterior probability $P(\omega_1|x_i)$; namely, the probability that the venture would be successful. This theory assumes that the training sample is a "pure random" sample.

Training refers to the process of determining the weights (including biases) so that SSE is as small as possible. Since this is a minimization problem, nonlinear programming methods can be used for training. Indeed, the networks are trained with the GRG2-based algorithm of Subramanian and Hung [1993]. GRG2 is a widely distributed nonlinear optimization system [Lasdon and Waren, 1986]. Subramanian and Hung [1993] show that this GRG2-based algorithm is much more efficient than back propagation.

The number of hidden nodes is an experimental factor. Theoretically, with a large number of hidden nodes, a neural network can approximate any function arbitrarily closely (see Hung, *et al.* [1996] for an explanation). The function to be approximated here is the posterior probability function. From this point of view, more hidden nodes are desirable. On the other hand, from the point of view of statistical estimation, more hidden nodes mean fewer degrees of freedom and the possibility of overfitting may arise. A rough analogue is multiple regression. Each time an independent variable is added to the function, one degree of freedom is lost because an extra coefficient is to be estimated. For neural networks, each arc weight is an unknown to be estimated. By adding a hidden node, several extra arcs are added. Statistically speaking, a small degree of freedom can mean overfitting in that the approximation is near perfect for the sample data but is not very good for the entire population. The question of the number of hidden nodes can only be answered experimentally with empirical data.

3.1 Model Building

The primary objective of this study is to build a model to predict Sino-Hong Kong joint venture performance. As in all modeling exercises, parsimony is an important criterion. It means that one wishes to achieve the highest degree of explanatory power with the smallest model. For this objective, two related questions need to be answered:

- What combination of variables will provide the best explanation for joint venture performance?
- What is the appropriate neural network model to use for this data set? For this study, this means the number of hidden nodes.

The best set of variables to use for explaining joint venture performance is determined by a backward elimination method. Starting with the full list of variables, a variable is eliminated one at a time until some stopping criterion is met. Let a neural network model be referred to as the "full" model and its sub-network be referred to as the "reduced" model. Here the reduced model is obtained by eliminating one input node and its associated arcs. Define

SSE_F = SSE of the full model

SSE_R = SSE of the reduced model

It should be that $\mathrm{SSE}_R \geq \mathrm{SSE}_F$ since the full model has more weights to adjust in order to reduce the objective value. In some instances, this relation might not hold because of the poor quality of solution for either the full or the reduced model, or both. The solution with the minimum SSE is then chosen for that particular model. This approach succeeded in producing the correct SSE's (as far as relative magnitude is concerned) for the models considered here.

The stopping criterion is based on the F-ratio of regression theory, which is

$$F = \frac{\frac{(SSE_R - SSE_F)}{(df_R - df_F)}}{\frac{SSE_F}{df_F}}$$

where df_R and df_F refer to the degrees of freedom of the reduced and full models, respectively. The degrees of freedom, in general, is defined as df=(number of observations - number of weights estimated).

Given a model, each input node and its associated arcs are eliminated and the F-ratio is calculated. The reduced model with the smallest F-ratio is chosen. If the F-ratio is less than a predetermined number, say F-OUT (which in this study is set at 6.00), then the corresponding input variable is eliminated.

The F-ratio has an F distribution only if the errors are normally distributed. There is no reason to believe that this assumption holds in neural network models. On the other hand, the F-ratio summarizes the contribution of an input variable to the "goodness-of-fit" of a network and so it seems like a good measure for comparing the value of variables.

4 Results

A training sample was randomly selected from the data set. Recall that there are 1,463 joint ventures, approximately 70% formed the training sample, giving a total of 1,024 observations with 98 successful

Hidden Nodes	Training SSE	MSE	Correct Classification	Test Correct Classification
7	64.32	0.0676	31+921=952	2+380=382
8	59.00	0.0626	44+921=965	4+373=377
9	60.41	0.0647	38+923=961	3+377=380
10	62.01	0.0670	38+924=962	0+326=326
Logistic Regression			1+926=927	0+397=397

Table 1: Classification Results for Training and Test Samples by Hidden Nodes

(Group 1) and 926 not-so-successful (Group 2) ventures. The remainder is the test sample, which has 439 observations: 42 successful and 397 not-so-successful ventures.

The question of what is the appropriate network to use is answered by varying the number of hidden nodes. The values used were from 1 to 10. Table 1 shows the results using the entire set of variables. It can be seen that SSE in the training sample decreases as the hidden nodes increase and reaches its minimum at 8 hidden nodes. It is interesting to note that correspondingly, classification rate in the training sample showed the same pattern. It reaches its maximum at hidden nodes being 8. In the test sample, highest overall classification rate is obtained with 1 hidden node with practically all the observations classified into group 2. With 8 hidden nodes, 4 observations, the largest number, were correctly classified in Group 1.

The issue of what is the appropriate set of explanatory variables to use is answered by a sequence of computations. First, backward elimination was used to reduce the number of variables. The network of 8 hidden nodes is chosen as the architecture and the training sample is the data set. When all variables are included, there are 8 input nodes, and the sum of squared errors, SSE_F,is 59.00 (Table 2). If variable PFINVEST (percent foreign ownership) is removed, then SSE_R is 67.28. The degrees of freedom are $df_F = 943$ and $df_R = 952$. This results in an F-ratio of 14.70. Table 2 shows that LOC is the prime candidate for elimination because it has the lowest F-ratio (5.59). Table 3 shows what happens after LOC is removed. If, in addition, PFINVEST is removed, the SSE_R becomes 70.00. Using the same original model as the full model, the F-ratio for this variable is 6.51. It can be seen at this stage that LDUR is the prime candidate for elimination. Table 4 then shows the results after both LOC and LDUR have been eliminated. Note that F-ratios are all greater than 6.00. The backward elimination procedure stops with PFINVEST, CAP, TECH, LPARTNER, and LINVEST in the model.

Variables Dropped	# input nodes	SSE	MSE	F-ratio	Training Classification	Test Classification
None	8	59.00	0.0626		44+921=965	4+373=377
PFINVEST	7	67.28	0.0707	14.40	23+919=942	2+376=378
CAP	7	62.35	0.0655	5.95	34+914=951	3+382=385
TECH	7	64.00	0.0672	8.87	35+925=960	4+385=389
LDUR	7	63.28	0.0665	7.60	26+920=946	2+378=380
LPARTNER	7	69.47	0.0730	18.58	25+921=946	4+366=370
LINVEST	7	71.74	0.0754	22.61	29+920=949	3+388=391
LOC	6	65.30	0.0680	5.59	23+925=948	2+382=384

Table 2: Full Model minus Variable Dropped

Variable Dropped	# Input Nodes	SSE	MSE	F-ratio	Training Classification	Test Classification
PFINVEST	5	70.00	0.0722	6.51	32+922=954	0+384=384
CAP	5	69.29	0.0714	6.09	21+924=945	3+383=386
TECH	5	66.01	0.0680	4.15	35+920=955	1+383=384
LDUR	5	65.02	0.0670	3.56	29+921=950	2+378=380
LPARTNER	5	68.91	0.0710	5.87	21+922=943	2+377=379
LINVEST	5	71.58	0.0738	7.44	18+923=941	2+388=390

Table 3: Full Model minus LOC minus Variable Dropped

Next, with these 5 variables in the model, we once again experimented with hidden nodes. Results are presented in Table 5. The architecture with 10 hidden nodes has the best classification rate in the test set and is chosen to be the final architecture for the data. Notice that 949 (92.68%) out of 1,024 of the observations were classified in training with 35 correctly classified in Group 1. In the test sample, 381 (86.79%) were classified having 2 observations correctly classified in Group 1.

In comparison, logistic regression with these five independent variables was conducted. Results in Table 5 show that in the training sample neural networks not only have a higher overall classification rate, 92.68%, compared to 90.43% for logistic regression, 35 observations were classified into group 1 while logistic regression failed to have any observation in this group. For the test sample, logistic regression again classified all observations into Group 2, maximizing the overall classification rate. As pointed out earlier, neural networks had 2 observations classified correctly in Group 1.

To check the final model recommended by neural networks, a similar backward elimination method is applied in the logistic regression models. The variable with the largest p-value is removed and the

Variable Dropped	# Input Nodes	SSE	MSE	F-ratio	Trainining Classification	Test Classification
PFINVEST	4	74.17	0.0758	6.73	15+922=937	0+378=378
CAP	4	72.84	0.0744	6.14	20+919=939	2+392=394
TECH	4	73.11	0.0747	6.26	14+923=937	0+391=391
LPARTNER	4	73.88	0.0755	6.61	14+920=934	1+382=383
LINVEST	4	78.22	0.0799	8.53	12+924=936	1+391=392

Table 4: Full Model minus (LOC, LDUR) minus Variable Dropped

Hidden Nodes	Training SSE	Training MSE	Training Classification	Test Classification
7	66.59	0.0682	28+921=949	1+382=383
8	65.02	0.0670	29+921=950	2+378=380
9	63.57	0.0659	34+915=949	2+377=379
10	62.83	0.0656	35+914=949	2+379=381
11	58.45	0.0614	40+919=959	0+378=378
12	57.51	0.0608	40+919=959	0+379=379
Logistic Regression			0+926=926	0+397=397

Table 5: Effect of Architecture for the 5 Variable Model

Method	Training Results			Test Results		
	Group 1	Group 2	Overall	Group 1	Group 2	Overall
Neural Network	14 (14.29)*	924 (99.78)	(91.60)	0 (0)	396 (99.75)	(90.21)
Logistic Regression	0 (0)	926 (100)	(90.43)	0 (0)	397 (100)	(90.43)

Table 6: Classification results based on model chosen by logistic regression (TECH, LPARTNER and LINVEST)

* Number correctly classified; percentage in parentheses

regression function recomputed. This procedure is repeated until no p-value is greater than 0.05. As shown in Table 6, this process results in three variables: TECH, LPARTNER, and LINVEST. With this set of variables, a neural network (8 hidden nodes) was trained and tested. It shows that, overall, neural network results are comparable to logistic regression, with slightly better results for Group 1 classification in the training sample.

The above results indicate that both neural networks and logistic regression are comparable. But logistic regression fails to identify any successful joint ventures in any model. But the more important thing is that neural networks produce estimates of posterior probabilities directly. With those values, one can vary the cost of misclassification to achieve desirable classification rates.

5 Conclusions

The use of neural networks in business applications is just now emerging. For this particular application in predicting the success of a joint venture, we believe the results are very interesting and will lead to further research on how the technique can be used for statistical testing purposes. Some previous research has indicated the performance of neural classifiers depends very much on the domain of applications. A neural networks user should first experiment on what architecture to use before finalizing on the results. Skipping this critical step will render neural classifiers less effective.

As noted in Table 1, neural classification has the best result in both the training and test samples when 9 hidden nodes were used. In addition, the disproportionate nature of the size of the two groups clearly brings out the dominance of neural classifiers over a traditional method like logistic regression. Neural networks correctly classifies 35 observations into the "successful" group in the training sample, compared to 0 observation by logistic regression (Table 5). A similar pattern is detected in the test set. Thus, logistic regression classifies all the observations in the training or test samples into the larger group. Therefore, even though the overall classification rate may be high, none of the observations in the smaller group is correctly classified.

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