Foreign Direct Investment in China:

Pre- and Post- Asian Financial Crisis

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Abstract

This paper will propose a genetic algorithm (GA) approach as an analytical tool with a carefully defined fitness function as a variable selection algorithm. Discriminant analysis will be used as a parameter evaluation method for the analysis of inward foreign direct investment (FDI) in China. Results indicate that Asian Financial Crisis does have some influences on FDI inflows to China, because two different variables have been selected, foreign loan and the growth rate of GDP. They present different attractive factors in Chinese economic environment.

1. INTRODUCTION:

Many countries see attracting foreign direct investment (FDI) as an important element in their strategy for economic development because FDI is widely regarded as an amalgamation of capital, technology, market, and management. For example, from 1979- May 2003, China attracted US $8431.99 billion in intended foreign direct investment (FDI), of which US $4605.59 billion (47%) has been realized (China Statistical Yearbooks, 1987-2003). FDI contributes to export, providing capital, technology, critical managerial skill, know-how, as well as creating needed employment. With the surge in FDI in the past decades, FDI once again has moved to the center of attention in policy discussions and in the literature on international economics and business. Most of the FDI researches in the past three decades have focused on the determinants of FDI. Even though there have been many studies, according to Dunning, there is no general theory of FDI and it does not make sense to look for a single all-embracing theory of FDI (Dunning, 1993). As such, model building and variable selection are carried out on a case by case basis depending on the specific situation of a country. Thus, this case by case approach makes the development of a general theory of FDI difficult.

To select the determinants of FDI, two traditional approaches are available: face to face interviews (O'connell, 1998); and statistical modeling. The limitation of interview-survey analysis is well defined in (Dunning, 1973). Moreover, this approach is limited due to firm specificity conditions. The statistical modeling is limited because relationship has to be assumed before knowing the nature and characteristics of the data. Riezman, Whiteman, and Summers (1996) have also pointed out that by omitting important variables, it can result in both "Type I" and "Type II" errors, that is, spurious rejection of one causality as well as spurious detection of it.

Therefore, to analyze determinants of FDI efficiently, a good strategy then is to take an interdisciplinary approach that combines statistics and machine learning algorithms, which can provide better economic data analysis and relationship discovering. This paper will propose a genetic algorithm (GA) approach as an analytical tool with a carefully defined fitness function as a variable selection algorithm and discriminant analysis method as a parameter evaluation method to be used in the analysis of inward FDI. The GA approach is a search procedure that uses random choice as a tool to guide a highly exploitative search through a coding of a parameter space (Jorge, 1998). The approach is based on the observation that the evolution of natural species is very efficient at adapting to changing environments. A GA approach can work on all the data types, different data set size, and different number of multiple data classes.

A GA approach can be applied to analyze many types of data, e.g. in industry: production planning, operations scheduling, personnel scheduling, line balancing, grouping order, sequencing, and siting. In financial services: risks assessment and management, developing dealing rules, modeling trading behavior, portfolio selection and optimization, credit scoring, and time series analysis. The applications of a genetic algorithm to mathematical optimization began with De Jong (1975) and originally were applied to problems in biology, engineering and operations research. Recent applications of GA for solving business and economic problems are, for example, analyzing the traveling salesman problems (Chatterjee and Lynch, 1996), solving product design problems (Balakrishnan and Jacob, 1996), simulating the ecology of oligopoly games (Chen and Ni, 1999), modeling the US consumer price index (Rabatin, 1999), financial classification (Berends, 1998), cost control analysis (Loughlin, 1998), individual welfare management (Weber, 1999), macroeconomic policies analysis (Rius, 1999), discovering trading rules in stock market (Chen, Lin, and Tsao, 1998) & (Chen, , Lin, and Tsao, 1999), and reconfigurable manufacturing systems designing (Son, 2000). However, up to now, none of the application was in the area of FDI.

In order to study inward FDI by adopting the GA approach, we will convert our analysis of FDI in China into a classification problem. This will enable us to apply the classification method consisting of a modified GA approach as proposed. In classification analysis, one of the main tests of a classification method is its ability to classify a set of data into different categories by using the most relevant decision variables. Moreover, classification method is not a new analytical approach in the analysis of inward FDI (see (Root and Ahmed, 1979), (Dunning, 1993), (Singh and Jun, 1995), and (Chen, 1997)). In recent studies (Berends, 1998), GA has been proposed as a good composite technique in classification problem by giving higher accuracy rate using less decision variables and in selecting an optimal variable subset among an initial variable set of larger size (Berends, 1998) & (Chtioui, Bertrand, and Barba, 1998). The GA approach is also good at exploring links and relationships in a quasi-automatic way and could indicate interesting or promising relationships. In short, GA could provide insight into group relationship among variables. These traits are very useful in economic analysis because an appropriate model may contribute not only in describing the patterns of financial or business data, but also in providing deeper theoretical understanding of economic problems. The purpose of proposing the GA approach into determinant analysis of FDI is to classify FDI efficiently and to find out the relationships among the independent variables and the dependent variable.

Another purpose of this paper is to study the differences between determinants of FDI inflows to China pre- and post- Asian Financial Crisis. The Crisis is a milestone event in Asian economy, and it not only slowdown the economic growth rate in Asia but also brought financial restructure as well as economic restructures to many Asian countries including China. Its effectiveness may sustain for decades. After the Crisis, FDI flows into China didn't reduce significant, moreover, it reaches the highest pick in recent years. So a question rises, what are the most important determinants, which attract FDI flows into China. Whether these factors have been changed after the Crisis due to a new investment environment in Asia? The study is going to analyze determinants of FDI inflows pre- and post- Financial Crisis to find out the differences between them.

2. GA METHODOLOGY:

Since the selection of relevant variables and the elimination of irrelevant variables are a central problem in classification analysis (Langley, 1994), which variables should be selected and which should be ignored, need to be carefully decided. There are two degrees of relevance for variables: strong and weak. Strong relevance implies that the variable is indispensable in the sense that it cannot be removed without loss of prediction accuracy. Weak relevance implies that the variable can only sometimes contribute to prediction accuracy. For finding and removing those weak "relevant" factors we follow the Kohavi model (Kohavi, 1995) as shown in Figure 1. This model is then used to develop an efficient classification method, which includes search and evaluation engines for the analysis of inward FDI.

As Figure 1 shows, we have a parameter search engine and a parameter evaluation engine. The model runs on the database, usually partitioned into training and test sets. The training set is used to decide the best subset of factors. And the test set is used to test how good the subset of variables performs. We call the former the training phase and the latter the test phase.

Different combinations of variable selection algorithm and variable evaluation method will generate different results and will have different prediction accuracy for classification problem. In this paper, we propose a GA approach as variable selection algorithm (parameter search engine) and discriminant analysis as the variable evaluation method (parameter evaluation engine). Further elaboration are given below:

A. Parameter search engine:

GA poses the potential solution of a problem as an individual--a set of parameters encoded as a string of binary bits. These parameters are like the genes of a chromosome, and they change order from generation to generation, much like genes in an actual chromosome. Standard GA manipulations, such as crossover and mutation, mix and recombine the genes of a parent population (mating pool) to form offspring for the next generation. Which offspring survive to the next generation is dictated by a fitness function. These problem-specific functions measure the degree of fitness to desirable parameters - it measures the goodness of a chromosome and decides which chromosome should be used to generate the next generation. In this process of evolution (manipulation of genes), the fitter chromosomes will create a large number of offspring, and thus have a higher chance of surviving to subsequent generations, emulating survival of the fittest in nature.

GA repeats this cycle until they reach a termination criterion. This criterion can be a fixed number of generations, the variation of individuals between different generations, or an expected fitness value. In the static population model, the algorithm is depicted in Figure 2 and can be explained as follow:

- ♦ Step 1: Generate an initial population of chromosome

(i). Define a representation of the chromosome for the given problem. Each chromosome is a binary string to represent a possible candidate solution to the problem. If one variable will be used in decision-making, it will be coded as “1”, otherwise it will be coded as “0”.

(ii). Design an objective function to evaluate the goodness of the chromosome for the given problem. This objective function is called a fitness function.

Generally, let $\boldsymbol{x}$ denotes a variable subset selected by GA during the training phase in classification analysis. For any N total number of instances, if there is C number of correct classification instances and $0 \leq C \leq N,$ the classification accuracy rate ACC is given as:

$$ACC\,(\boldsymbol{x}) = \frac{C(\boldsymbol{x})}{N} \qquad \text{Eq. 1}$$

For the variable subset selection problem, the traditional and simplest choice of measurement used to calculate the **fitness function [f(x)]** is classification performance. Hence,

$$f(\mathbf{x}) = ACC(\mathbf{x}) \qquad \text{Eq. 2}$$

(iii). Generate a set of initial chromosomes (initial population of chromosomes). This initial population of chromosomes could be generated on the random basis or selected from results of previous studies on FDI such as in (Dunning, 1993) or (Chen, 1997).

- Step 2: Reproduction

(i). Calculate the fitness value for each chromosome of the generated population.

(ii). Discard the chromosome with the lowest fitness values and copy once/or more than once those chromosomes which have the highest fitness value to generate the next generation chromosome as their offspring, depending on the fitness value of chromosome and selection rules (i.e. the best get more copies, the average stay even and the worst die off).

- Step 3: Crossover operation

Randomly select two chromosomes as parents in current generation of population. This operator randomly selects a point with certain probability, called crossover rate, and exchanges the remaining segments of both parents to create the new offspring. This crossover rate could be any desired rate or rate based on some previous studies.

- Step 4: Mutation

To avoid losing some potentially useful genetic material (1's or 0's at particular locations), mutation operation was introduced. In the simple GA model, mutation is the occasional (with small probability - mutation rate – say 0.001) random alteration of the value of a string position, i.e. changing from 1 to 0 or 0 to 1.

♦ Step 5: Stopping criteria

Repeat steps 2 to 4 until certain criteria are met. These criteria can be a fixed number of generations, say 20, or the variation of individuals between different generations (e.g. when subsequential five generations gave similar results, we could stop the computation as we may not be able to improve the result further). We could also stop the computation when an expected fitness value decided on a prior is reached.

B. Parameter evaluation method:

As part of the proposed GA method, we use discriminant analysis as parameter evaluation method to remove weak relevant variables. The multiple discriminant analysis is chosen as a comparison method because it has been applied by (Root & Ahmed, 1979) and (Chen and Chen 1998) in analyzing determinant of FDI.

3. Methodology:

♦ Dependent variable

Since FDI has been one of the four engines of Chinese economic development during the last two decades, both Chinese central and local governments are eager to attract as much FDI as possible. The total quantity of inward FDI then becomes a measure for determining whether a province has done well in attracting FDI. Usually, a province has done well when it attracts more FDI inflows than before within the resource allotted. Success is judged relative to comparable objectives. The absolute value of FDI per se is not so meaningful in this analysis. To measure its importance and contribution to economic development, FDI over GDP is used as the analytical dependent variable. In this paper, the dependent variable is defined as the percentage of FDI inflows to different Chinese provinces (PFDI). It is equal to total FDI inflow to a province divided by GDP in the province:

$$\text{PFDI} = \frac{\text{FDI inflow}}{GDP} \qquad \text{Eq. 3}$$

In analyzing FDI using classification method, dependent variables in existing studies are classified into several groups according to certain criteria. In this paper, we will classify PFDI into two classes: successful inflow or unsuccessful inflow. Successful inflow refers to higher FDI inflows ratio to a region compared with a cutting point decided a priori and unsuccessful inflow refers to lower FDI inflows ratio to a region compared with the cutting point. The rationale for classifying successful and unsuccessful inflows is that we want to measure the region's performance in attracting FDI inflows compared with some chosen benchmarks. As the focus of this paper will be on the different regions of China, and while we assume that all regions are facing the same macro-economic environment, legal structure and country risk, different regions still differ in terms of infrastructure, resource availability, R&D intensity and industrial agglomeration. Because of this, we expect that their performance in terms of attracting inward FDI will be different.

♦ Independent variables

In our study, we treat factors that affect FDI into a particular province as independent variables. Independent variables are derived from previous literature as well as taking into consideration the FDI environment in China. From literature review, a total of 30 variables considered important to FDI are listed in Table 1.

♦ Proposed fitness function

In order to select the most relevant variables and improving prediction accuracy, in this paper we propose a new fitness function [F(x)], which used a multi-objective fitness function instead of a traditional one, e.g. equation (1), to avoid including weak relevant variables.

$$F(x) = c_1 \times [\, c_2 \times (\frac{1}{n}\sum_{i=1}^{n} r_i^2) + (1 - c_2) \times \rho_{y,x1,x2,\ldots,xp} \,] + (1 - c_1) \times A_{cc} \qquad \text{Eq. 4}$$

The proposed fitness function consists of three parts. The first part, r_i^2, is correlation coefficient between independent variables x_i and dependent variable y. The greater the value of r_i^2 means that the independent variable x_i is more related to the dependent variable y. r_i^2 is used to control the number of variables that will be in our final subset. This means that if we can select the most relevant variables to be included in our final variable subset, this will contribute to a higher value to the fitness function. The range of r_i^2 is [0 1].

The second part, $\rho_{y,\ x1\ldots xp}$, is the multiple correlation coefficient, which indicates the linear association between the selected group of independent variables x_1, x_2, …, x_p, and dependent variable y. The range of the multiple correlation coefficient is $0 \le \rho \le 1$. A value of zero indicates that y is independent of the set $\{x_1, x_2, \ldots, x_p\}$, while a value of 1 indicates perfect linear association, that is, y can be expressed exactly as a linear combination of $\{x_1, x_2, \ldots, x_p\}$, with no error. If we select the most relevant group of independent variables, it will contribute to higher value to the fitness function.

Finally, A_{cc} takes care of classification accuracy; if the selected variable subset can give high prediction accuracy, the higher is the value of the fitness function. c_1 and c_2 are weight factors, which are used to differentiate relationship that we want to emphasize. To illustrate, if we choose a smaller value of c_2, it means that we think the linear association between group variable x_1, x_2, …, x_p and decision variable y is more important, otherwise we need to choose a bigger value for c_2. The range of variables c_1 and c_2 is [0 1].

- Cutting points: 3.23% (average value of FDI/provincial GDP in China from 1992 to 1998)
- Model illustration

The objective of the model is to explore which group of independent variables can better determine successful or unsuccessful FDI inflow. The general procedure of the GA model in the study is illustrated in Figure 3 and can be explained as follow:

A binary strings will be used to represent the 30 independent variables mentioned earlier that impact on the dependent variable, i.e. FDI inflow/GDP (PFDI). In any string, if a variable is used (e.g. x_i) as a criterion in classification, then '1' was put in the i^{th} position of the string; otherwise, '0' would be used. To illustrate, the study assumes one string in which all odd numbers are used in the classification decision. Then, it can be represented as a binary string '101010101010101010101010101010'. This string means that only variables 1, 3, 5, 7, …, and 29 will be used as criteria in classification. Then the study generates the initial population randomly and the genetic algorithm method uses a standard parameter setting. The different parameter settings cause different results. In order to determine the result, the study adopted an efficient parameter setting provided by De Jong [11], as follows:

Population size	50
Crossover rate	0.6
Mutation rate	0.001

The multiple discriminant analysis is used as a parameter evaluation engine to calculate the fitness function value and generate the next generation using GA as a parameter search engine. Step 2 to 4 given in methodology were repeated, until 20 generations were reached or until 5 generations gave similar results.

The final subset of decision variables is presented by a binary string (for example the string displayed above: 101010101010101010101010101010). If the accuracy rate (Acc) is 95%, it means that if variable 1, 3, 5, 7, 9, …, and 29 are used to classify new dependent variable (FDI inflow ratios), 95% of such classification would be correct.

4. RESULTS AND CONCLUDING REMARKS:

Starting with 30 variables as shown in Table 1, Table 2 shows that these two samples provided a quite similar result, saying, only one different variable out of 14 final decision variables is selected in final results provided by these two samples. These two different variables selected by two samples are foreign loan (Pre- Financial Crisis) and the growth rate of GDP (Post- Financial Crisis).

Some researchers have proved that as a milestone event, Asian financial crisis didn't have negative effect on FDI flows into Asian countries. Bartels and Mirza (1999) argue that pre- and post-Crisis patterns consistently support unchanged commitment to Asia. Their evidence supports their view that the Asian Crisis has not dented seriously the confidence of MNCs either in Asia or in their own organizational capabilities. Ironically, the Crisis, in forcing faster deregulation and liberalization, has created opportunities for mergers and acquisitions. Their argument may support those identical variables in our results.

But compared with Bartels and Mirza's study, our study finds two different variables between these two samples of pre- and post- Asian Financial Crisis. So it could be concluded that the difference between these two samples is caused by whether includes influence of Asian financial crisis or not. In other words, Asian

Financial Crisis does have some influences on FDI inflows to China. Now, let's see these two variables one by one.

Firstly, let's see the sub-sample before crisis. It includes one special variable, foreign loan. World Bank Report (1999) argued that the critical immediate vulnerability came from an excessive buildup of short-term foreign currency debt on the balance sheets of private agents. This debt made countries vulnerable to sudden swings in international capital market sentiment. As we know, it was one of main reasons caused Asian financial crisis in 1997. Although foreign loan especially short-term foreign currency debt was not too significant to cause financial crisis in China, it cannot be ignored in our study especially after Asian financial crisis. But as we have seen in our results, it is no longer a determinant for China after crisis. This phenomenon indicates that China gets experiences from financial crisis and restructures its financial system during financial crisis. The new investment environment must be better for China's further economic development. According to experiences gotten from Asian financial crisis, compared with international indirect investment, e.g. foreign loan, it is found that direct investment can contribute more to long-term economic growth. It is because those direct investments won't crowd in or crowd out at the same time.

Secondly, let's see the sub-sample after crisis. It includes another special variable, growth rate of GDP. It means that after financial crisis, a faster growing market is more attractive for foreign investors than before. This is an unsubstitutable advantage in China and it could support sustained development in long term.

According to these two variables, foreign loan and growth rate of GDP, we cannot conclude that financial crisis has no effect on FDI flows into Asia, especially into China, although the majority of determinants of FDI inflow to China didn't change. We have to say among determinants, what have been changed have significant influence on China, even for the whole Asia.

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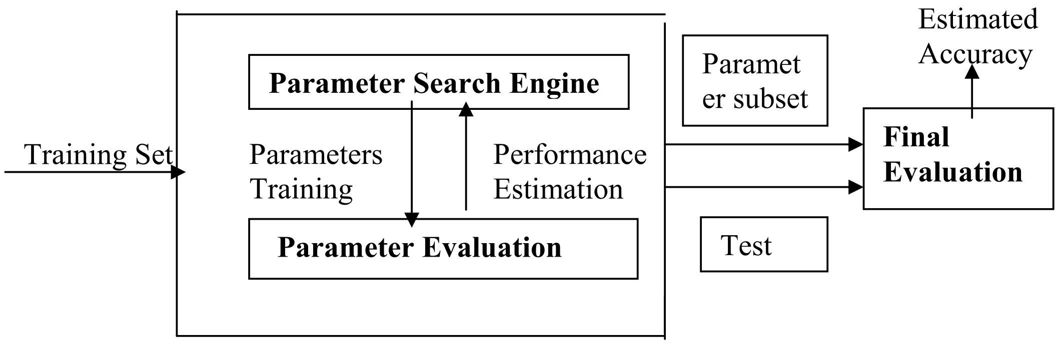

Figure 1 Kohavi model for variable selection

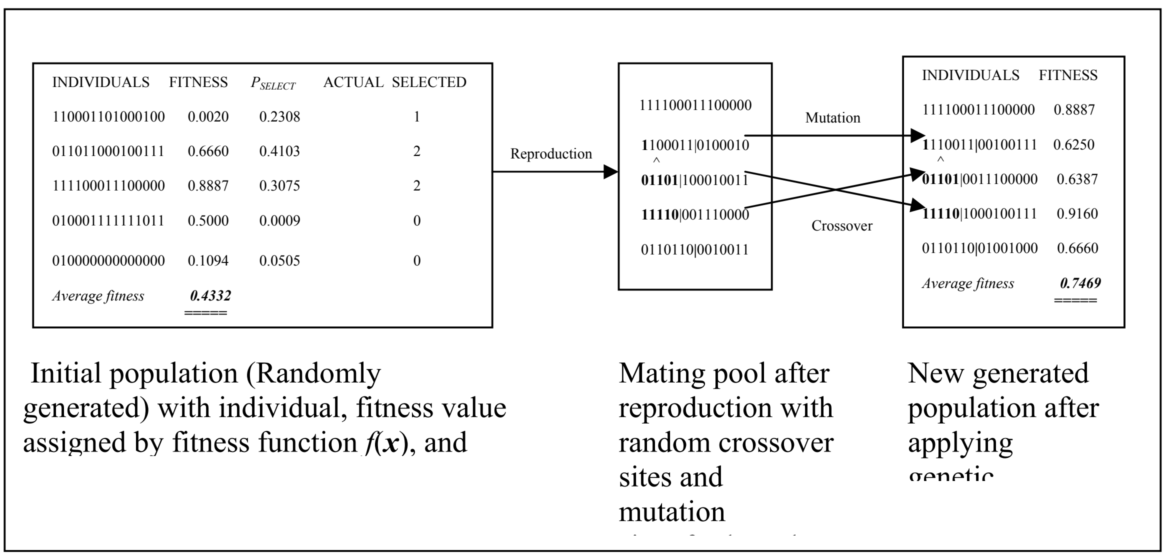

Figure 2 Working process of GA approach

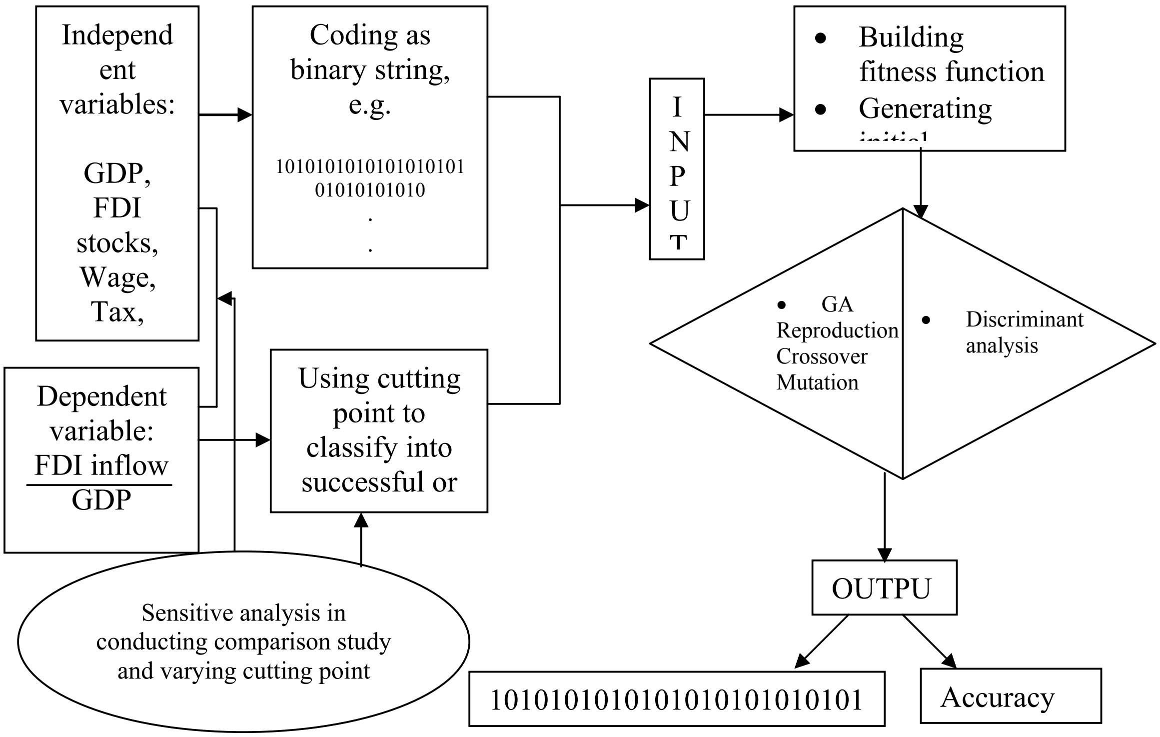

Figure 3 Proposed Conceptual GA Model

Table 1 Variables that affect FDI in different regions of China

Market size and Economic growth factors in provinces
V1. Population size
V2. Potential market size (Growth rate of provincial GDP)
V3. Economic development level (Per capita consumption)
V4. Provincial market size (Total sales in provincial market)
V5. Price stability (Consumer price indices)
V6. International market orientation (Export value to provincial GDP)
Infrastructure development of provinces
V7. Total investment in fixed assets
V8. Turnover freight traffic (Density of freight traffic)
V9. Transportation intensity (Length of highway, railway and trunk railways)
V10. Telecommunication intensity (Business volume of postal and telecommunications service)
V11. Size of government (provincial government contribution to provincial GDP)
Living condition in provinces
V12. Education facility (Children education)
V13. Service facility (Medical service)
Labor cost in provinces
V14. Wage rate
Profitability of enterprises in provinces
V15. ROA (Return on assets)
V16. ROS (Return on sales)
The level of openness in provinces
V17. Degree of openness
V18. No. of hotels for foreigners
R&D intensity in provinces
V19. Transaction value in technology market
V20. R&D manpower
V21. R&D investment
V22. No. of patents applied in that year
Environmental issues in provinces
V23. Environment related cost (Output value of products made from utilization of waste gas, water and industrial residue)

V24. Environment related profit (Profit obtained from utilization of waste gas, water and industrial residue)
Overall investment environment in provinces
V25. FDI stocks (The level of accumulated FDI stocks)
Policy incentive in provinces
V26. Government incentive (government financial subsidy) V27. Tax rate
Other variable in provinces
V28. Amount of foreign loan
Industrial agglomeration in provinces
V29. Composition of tertiary industry to provincial GDP V30. Gross output value of industry to provincial GDP

Table 2 Final Selection of decision variables

Variables	92-96	92-98
1		
2		1
3	1	1
4		
5		
6	1	1
7	1	1
8		
9	1	1
10	1	1
11		
12		
13		
14	1	1
15	1	1
16		
17	1	1
18		
19	1	1
20	1	1
21	1	1

22		
23	1	1
24		
25	1	1
26		
27	1	1
28	1	
29	1	1
30	1	1