Expert Systems with Applications 40 (2013) 2366–2372

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Estimating discretionary accruals using a grouping genetic algorithm

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ARTICLE INFO

Keywords:
Earnings management
Discretionary accruals
Genetic algorithms

ABSTRACT

A number of different models have been suggested for detecting earnings management but the linear regression-based model presented by Jones (1991) is the most frequently used. The underlying assumption with the Jones model is that earnings are managed through accounting accruals. Typically, the companies for which earnings management is studied are grouped based on their industries. It is thus assumed that the accrual generating process for companies within a specific industry is similar. However, some studies have recently shown that this assumption does not necessarily hold. An alternative approach which returns a grouping which is, if not optimal, at least very close to optimal is the use of genetic algorithms. The purpose of this study is to assess the performance of the cross-sectional Jones accrual model when the data set firms are grouped using a grouping genetic algorithm. The results provide strong evidence that the grouping genetic algorithm method outperforms the various alternative grouping methods.

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1. Introduction

The occurrence of earnings management has been a widely studied subject for the past 30 years. One of the major challenges when examining possible earnings management is that the magnitude of it is difficult to assess. A number of different models have been suggested for detecting earnings management but the linear regression-based model presented by Jones (1991) is the most frequently used. The underlying assumption with the Jones model is that earnings are managed through accounting accruals. Typically, the companies for which earnings management is studied are grouped based on their industries. It is thus assumed that the accrual generating process for companies within a specific industry is similar. Recently, however, some studies have shown that this assumption does not necessarily hold. Dopuch, Mashruwala, Seethamraju, and Zach (2012), for example, showed that a violation of the homogenous accrual generating process within an industry causes measurement errors. In another study Ecker, Francis, Olsson, and Schipper (2011) showed that the performance of the Jones model is improved when lagged total assets are used as a grouping variable instead of the industry membership. Even though alternative methods have been used for grouping companies when using the Jones-model, none of them has clearly outperformed the grouping based on industry membership.

An exhaustive search for the best possible grouping is in most cases impossible considering the large number of possible combinations even with moderate size data sets. An alternative approach that returns a grouping which is, if not optimal, at least very close to optimal is the use of genetic algorithms. Genetic algorithms have proven efficient in solving difficult problems such as the travelling salesman and the equal piles problems.

Genetic algorithms have been used in a number of accounting applications. Back, Laitinen, and Sere (1996) used a genetic algorithm to determine the optimal predictors for a neural network-based bankruptcy prediction model. A similar study was carried out by Shin and Lee (2002) when they used a genetic algorithm to generate bankruptcy prediction rules. Hoogs, Kiehl, Lacomb, and Senturk (2007) presented a genetic algorithm approach for detecting financial statement fraud. Their model successfully classified 63% of the companies that had been accused by the Securities and Exchange Commission (SEC) for improperly recognizing revenue.

The purpose of this study is to assess the performance of the cross-sectional Jones accrual model when the data set firms are grouped using a grouping genetic algorithm. The performance of the grouping genetic algorithm approach is compared with the performance of a number of other grouping techniques.

The remainder of this study is organized as follows. The basic operating principle of the linear regression-based accrual models is covered in Section 2. In Section 3 an overview of both classic and grouping genetic algorithms is given. The research design is presented in Section 4 and the results from the empirical study are presented in Section 5. Section 6 concludes the study.

2. Discretionary accrual estimation models

Several approaches for measuring the extent of earnings management have been proposed but the method that has gained the

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http://dx.doi.org/10.1016/j.eswa.2012.10.048

widest acceptance among researchers is the linear regression-based model presented by Jones (1991). The general assumption with the Jones-model is that earnings are managed through accounting accruals. The accruals are defined as the difference between net earnings before extraordinary items and cash flows from operations. The purpose of the Jones-model is to split the total accruals of a company into non-discretionary (expected) and discretionary (unexpected) accruals. The non-discretionary accruals are accruals that the company management has no or little control over, whereas the discretionary accruals are a proxy for earnings management. In the model the reciprocal of total assets, change in revenues (ΔREV) and gross property, plant and equipment (PPE) are regressed on total accruals (TACC). The variable for change in revenues controls for current accruals such as receivables, payables and inventory whereas the variable for property, plant and equipment mainly controls for depreciation and amortization accruals. In the linear regression-based Jones-model the regression error term (ε) equals the discretionary accruals

$$\frac{\mathrm{TACC}_t}{\mathrm{TA}_{t-1}} = \beta_0 \frac{1}{\mathrm{TA}_{t-1}} + \beta_1 \frac{\Delta\mathrm{REV}_t}{\mathrm{TA}_{t-1}} + \beta_2 \frac{\mathrm{PPE}_t}{\mathrm{TA}_{t-1}} + \varepsilon$$

In the original Jones-model the regression was run separately for each company using a time-series of at least 10 observations. The time-series approach has, however, several drawbacks. First, the requirement of at least 10 years of financial statement data might lead to both a survivorship bias and a selection bias (Jeter & Shivakumar, 1999). Second, the assumption that the accrual generating process of a company is stable over longer periods of time does not necessarily hold (Dopuch et al., 2012). Due to these drawbacks the time-series approach has largely been replaced by the cross-sectional approach first suggested by Dechow (1994). With the cross-sectional approach it is assumed that companies within a specific industry have a similar accrual generating process. Usually the industry is defined at a two-digit level SIC (e.g. Bartov, Gul, & Tsui, 2000; Jeter & Shivakumar, 1999). A number of recent studies have questioned whether the assumption of similar accounting generating processes within the industries is valid. Dopuch et al. (2012) showed that the assumption of a homogenous accruals generating process does not apply for several industries. Furthermore, they also showed that the violation of this assumption caused some measurement error of discretionary accruals. They do not, however, suggest any alternative method of grouping the companies when using the Jones-model. Ecker et al. (2011) used a number of different variables for grouping companies when using the Jones-model and their findings showed that the best result was achieved when lagged total assets were used.

3. Genetic algorithms

3.1. Operating principle

Genetic algorithms are an optimization technique based on models of natural selection and evolution. The fundamental principles of the genetic algorithm were first presented by Holland (1975). The starting point when using genetic algorithms is a population consisting of a certain number of chromosomes (individuals), where the chromosomes represent valid solutions to the problem. Once the population size has been determined, the initial population is usually randomly generated. The size of the initial population depends on the complexity of the problem. A genetic algorithm with a smaller population is faster but at the same time the risk of premature convergence increases (Koljonen, Mannila, & Wanne, 2007). Once the initial population has been generated, the fitness of each chromosome is evaluated. Based on the fitness values, parent chromosomes are selected from the initial population to form new chromosomes to the next generation through a breeding process. The most commonly used method for selecting the parent chromosomes is the roulette wheel selection (Butun, Erfidan, & Urgun, 2006) in which a proportion of the wheel is assigned to each chromosome based on their fitness values. The larger the proportion of the wheel, the higher the probability of getting selected. A central part of the breeding process is the cross-over function. The parent chromosomes are combined using a cross-over function to form new chromosomes. A commonly used cross-over technique is the single-point cross-over where a single cross-over point is selected in the chromosome. The part beyond the cross-over point is then swapped between the two parent chromosomes. Once the next generation has been formed, the new chromosomes are subjected to random mutation. The purpose of the mutation is to prevent the premature convergence of the genetic algorithm. After the mutation process has been completed, the fitness of the chromosomes in the new generation is assessed and the selection and cross-over procedures start all over. The evolution process is stopped when a satisfactory solution has been reached or when some other predetermined condition has been met. To prevent from losing the best chromosomes during the cross-over and mutation operations, elitism can be employed. Elitism means that the best or a few of the best chromosomes are directly copied from the previous to the next generation. Elitism can improve the performance of the genetic algorithm but there is also a risk that it leads to premature convergence.

3.2. Grouping genetic algorithms

Classic genetic algorithms do generally not perform well on grouping problems. The main problems are a high redundancy among the population chromosomes and a context insensitivity of the cross-over function (Falkenauer, 1996). To deal with these shortcomings of the classic genetic algorithm, Falkenauer (1992) suggested a modified genetic algorithm suited for grouping problems. The general difference between the two types of genetic algorithms is that in classic genetic algorithms the focus is on individual items whereas in grouping genetic algorithms the focus is on groups of items.

In a grouping genetic algorithm the chromosome is divided into a number of groups which in turn contain a number of individual items. The values of the individual items as such are not important. Instead, it is the group membership of the items that is of value. In the grouping genetic algorithm suggested by Falkenauer, the chromosome length is variable. The grouping genetic algorithm can, however, also be used with fixed length chromosomes when required by the nature of the problem (e.g. the equal piles problem, Falkenauer, 1996).

The cross-over function for the grouping genetic algorithm is illustrated in Fig. 1. First, two cross-point are selected randomly in both chromosomes involved in the cross-over function. To generate the first new chromosome, the genes between the cross-points in the second old chromosome are injected after the first cross-point in the first old chromosome. At this point some items occur in two groups. The groups coming from the first old chromosome and that have items also occurring in the groups coming from the second old chromosome are deleted. After removing these groups, some items might not be present in the remaining groups. These items are allocated to new groups using various methods. The missing items can, for example, form a new group or they can be distributed over a certain number of new groups. Once the first new chromosome has been created, a second new chromosome is formed using the same two old chromosomes but in a reverse order.

As with the cross-over function, the mutation operator for grouping genetic algorithms works on groups rather than items.

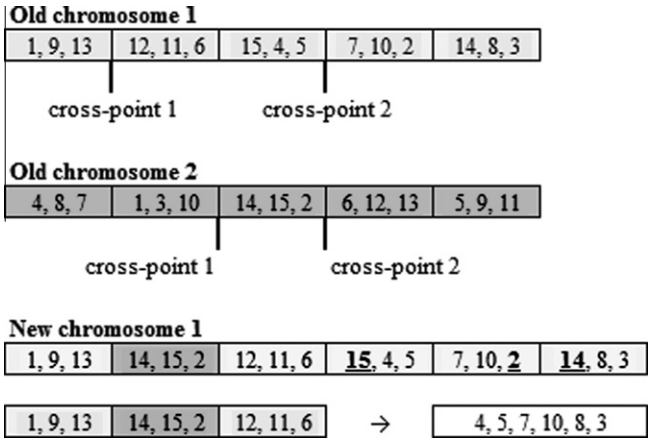

Fig. 1. Grouping genetic algorithm cross-over function.

Falkenauer (1996) describes three general strategies for mutation for the grouping genetic algorithm: creating new groups, eliminating existing groups or shuffling a small number of randomly selected items among the groups. The exact implementation details depend on what type of a problem is to be solved.

4. Research methodology

4.1. Research task

The purpose of this study is to assess the performance of the cross-sectional Jones accrual model when the data set companies are grouped using a grouping genetic algorithm. The results obtained with the grouping genetic algorithm approach are compared with results obtained with various other grouping techniques, such as grouping the companies by their two-digit SIC. The performance of the cross-sectional Jones model with the different grouping techniques is measured both by the standard deviation of the discretionary accruals as well as by the ability to detect simulated earnings management of various levels.

4.2. Data set description

The data set comprises financial statement data for public US companies with complete data for years 2009 and 2010 retrieved from Burea van Dijks Orbis database. In accordance with previous studies, utilities (SIC 4900-4999) and financial companies (SIC 6000-6999) are excluded from the data set. Furthermore, companies with lagged total assets less than 1 million USD, zero revenues for at least one of the two years, absolute total accruals equal to or above lagged total assets or market capitalization equal to zero are removed. To avoid the impact of possible outliers, the independent variables in the Jones-model (change in sales and property, plant & equipment) are truncated at the 1st and 99th percentiles. Finally, all companies belonging to two-digit SIC groups with less than 20 companies are excluded. The criteria above results in a data set comprising 2590 companies in 30 two-digit SIC groups. The final data set contains 10 groups with 20 companies with the same two-digit SIC in each group (see Table 1). These 10 groups are selected randomly out of the available 30 two-digit SIC groups. If a selected group has more than 20 companies, 20 companies are selected randomly from all companies with the same two-digit SIC. The following 10 two-digit SIC groups have been randomly selected.

Table 1
Data set structure.

Two-digit SIC	Description	*n*
26xx	Paper and allied products	20
28xx	Chemicals and allied products	20
33xx	Primary metal industries	20
34xx	Fabricated metal products	20
36xx	Electronic and other electrical equipment and components	20
39xx	Miscellaneous manufacturing industries	20
42xx	Motor freight transportation and warehousing	20
58xx	Eating and drinking places	20
79xx	Amusement and recreation services	20
82xx	Educational services	20
		200

4.3. Grouping genetic algorithm discretionary accrual model

The discretionary accrual model used in this study is a linear regression-based cross-sectional version of the Jones-model (e.g. Dechow, 1994). In the model the reciprocal of total assets, change in revenues (ΔREV) and gross property, plant and equipment (PPE) are regressed on total accruals (TACC). Total accruals are calculated by subtracting operating cash flows from net earnings before extraordinary items. All variables in the regression equation are deflated by lagged total assets (TA_{t-1})

$$\frac{TACC_t}{TA_{t-1}} = \beta_0 \frac{1}{TA_{t-1}} + \beta_1 \frac{\Delta REV_t}{TA_{t-1}} + \beta_2 \frac{PPE_t}{TA_{t-1}} + \varepsilon$$

The grouping genetic algorithm is used for dividing the data set companies into 10 groups with 20 companies in each. For each of the 10 groups the Jones-model regression model is run separately. The residuals from the regressions (ε) equal the discretionary accruals and the fitness of a specific grouping is assessed based on the standard deviation of the discretionary accruals for all 10 groups combined. The lower the standard deviation of the discretionary accruals, the better the grouping of the companies.

The parameters for the genetic algorithm are presented in Table 2. There is no exact method for determining the parameters and thus some heuristics are required. Both the number of groups and the group size (number of items per group) are fixed and do not change during the evolution process. The population comprises 100 chromosomes which are initially generated at random. The maximum number of generations is set to 25,000 but the evolution process is stopped if the best fitness value reaches zero. In order to prevent the loss of the chromosomes with the best fitness, elitism is employed. In this study, the chromosomes with the 10 best fitness values are copied directly to the next generation. To avoid getting stuck in local minima and to prevent early convergence, a mutation mechanism is used. The probability that a chromosome is mutated is set to 5%. The chromosomes selected by elitism are excluded from possible mutation.

When generating a new generation with the genetic algorithm, the chromosomes with the 10 best fitness values are first copied from the old generation. The remaining chromosomes are generated from chromosomes in the old generation using the roulette wheel selection and a cross-over mechanism so that two chromosomes from the old generation results in two chromosomes in the new population. The cross-points in both chromosomes are selected randomly. Once the new generation is completed,

Table 2
Genetic algorithm parameters.

Parameter	Value
Population size	100
Maximum number of generations	25,000
Mutation probability	0.05
Elitism	10
Number of groups	10
Observations per group	20

the chromosomes are subjected to possible mutation. If a chromosome is mutated, two genes are randomly selected from the chromosome and the items in these genes are randomly shuffled.

4.4. Strategy of analysis

The performance of the Jones-model when grouping the companies using a grouping genetic algorithm is compared with the performance of a number of alternative grouping methods. First, the performance is assessed when the companies are randomly grouped and when one regression is run for all 200 companies pooled. Second, the companies are grouped based on their two-digit SIC. This is a common method of grouping, used frequently in previous studies. Last, six other grouping variables suggested by Ecker et al. (2011) are used. These six variables are current and lagged total assets, current and lagged revenues, market capitalization and company age in years. When forming the groups using these six variables, the companies are first sorted according to the value of a variable. The first group then consists of companies 1–20, the second group of companies 21–40 and so forth.

The performance of the different grouping methods is first assessed by comparing the standard deviation of the discretionary accruals. A lower standard deviation of the discretionary accruals equals a better performance. Furthermore, the mean and median values of the discretionary accruals are examined. The closer to zero these values are, the better the performance of a method. To assess the earnings management detection ability of the different grouping methods, various levels of simulated earnings management are inserted to the data set. Two types of earnings management are simulated: expense manipulation and revenue/bad debt-manipulation. In expense manipulation a certain level of earnings management is added to total accruals, whereas in revenue/bad-debt manipulation earnings management is added both to the total accruals and to the change in revenues. The levels of the simulated earnings management ranges between −5% and 5% of lagged total assets with 1% increments. To test whether a grouping method is able to detect a certain level of earnings management, simulated earnings management is added to 20 companies which are randomly selected from the total data set of 200 companies. The discretionary accruals for the companies with the simulated earnings management are calculated using the regression coefficients for the group to which they belong. Furthermore, for the 20 companies that have simulated earnings management a partitioning variable (PART) is set to 1. For the remaining 180 companies the partitioning variable is set to 0. Next, the partitioning variable is regressed on the discretionary accruals (DACC)

$$\frac{\mathrm{DACC}_t}{\mathrm{TA}_{t-1}} = \beta_0 + \beta_1 \mathrm{PART} + \varepsilon$$

The ability of the Jones-model to detect certain level of simulated earnings management when using a specific grouping method is determined based on the regression coefficient of the partitioning variable (β_1). If the β_1 coefficient is significant at a 5% level, the simulated earnings management is considered detected. The earnings management simulation process is repeated 500 times. The performance of a specific grouping method is assessed based on the number of significant coefficients for the partitioning variable at different levels of simulated earnings management.

5. Results and discussion

5.1. Descriptive statistics

The total data set consists of 200 public US companies from 10 different industries. The descriptive statistics presented in Table 3 show that there are considerable differences between the data set companies. The largest company has total assets of more than 39 billion USD, whereas the smallest company shows total assets of just above 1 million USD. Similarly, the revenues range between more than 25 billion USD and about 15000 USD. The average total accruals are −0.069. This is expected as accruals typically are negative due to depreciation. The age of the companies ranges between 1 and 155 years, with an average age of 35 years.

The evolution process is illustrated in Fig. 2. The dotted line shows the average standard deviation of the discretionary accruals and the solid line shows the lowest standard deviation of the discretionary accruals for the population in each generation. At around the 6000nd generation the population starts to converge and from the 10,000nd generation and onwards only minor improvements to the lowest standard deviation of the discretionary accruals occur. When the evolution process is stopped at the 25,000nd generation the lowest value of the standard deviation of the discretionary accruals is 0.060. The evolution process was also run using various parameter values for population size, elitism and mutation probability. The evolution processes with the alternative parameters did, however, not improve the results.

5.2. Assessing the performance of the model

In this study the performance of the cross-sectional Jones-model is assessed with the companies grouped using a grouping genetic algorithm. The performance of the genetic algorithm grouping method is compared with the performance of nine other grouping methods. The first test of performance is based on the standard deviation of the discretionary accruals. The results in Table 4 clearly show that the genetic algorithm grouping method has the lowest standard deviation at 0.060. The second best grouping method is the two-digit SIC grouping with a standard deviation of 0.115 whereas the worst performing grouping method is the pooled regression with a standard deviation of 0.146. The remaining seven grouping methods show similar standard deviations ranging between 0.130 and 0.136.

None of the 10 grouping methods show discretionary accruals significantly different from zero. The grouping method with the mean discretionary accruals closest to zero is the genetic algorithm grouping method, whereas the grouping method based on the market capitalization shows the median discretionary accruals closest to zero. Finally, the genetic algorithm grouping method clearly shows the smallest values for both minimum and maximum discretionary accruals. Overall, these results show that the genetic algorithm grouping method outperforms the other nine grouping methods.

In the second test of performance, known levels of earnings management is added to 20 companies which are randomly selected from the total data set of 200 companies. The levels of the simulated earnings management ranges between −5% and 5% of lagged total assets with 1% increments. For each level of simulated earnings management, 500 data sets with 20 randomly selected companies are created and evaluated. The higher the number of data sets where earnings management is detected, the better the performance. The results from the simulated expense manipulation are presented in Table 5. With no simulated earnings management, a well specified model is not expected to detect any earnings management in a randomly selected data set. When no simulated earnings management has been added to the data set, the detection rate varies between 4.4% and 7.8%. As expected, the higher the level of the simulated earnings management, the higher the detection rate is for all grouping methods. At a level of ±1% the genetic algorithm grouping method shows the highest detection rates but the difference to the other grouping methods is not distinct. However, already at a level of ±2% the difference between

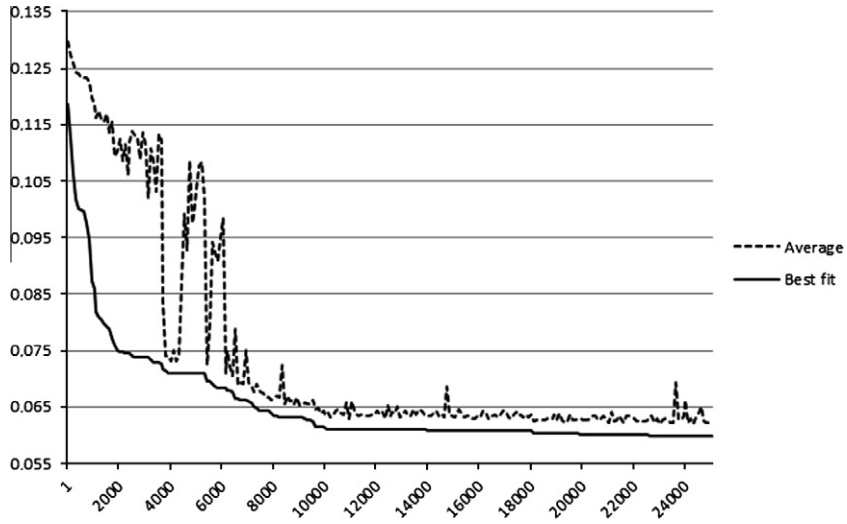

Fig. 2. Average and best standard deviation of discretionary accruals.

Table 3
Descriptive statistics for data set companies.

$n = 200$	Total assets t	Revenues t	Market cap. t	Total accruals t	Firm age (years)
Mean	1639.6	1397.2	1342.8	−0.069	35
Median	327.1	331.4	240.5	−0.062	25
St. dev.	4245.3	3024.5	3093.3	0.150	29
Min	1.3	0.0	0.1	−0.869	1
Max	39293.0	25179.0	22984.0	0.675	155

The data presented in the table is 2010 data.

Table 4
Descriptive statistics for discretionary accruals.

	All	Two-digit SIC	Total assets t	Total assets $t-1$	Sales t	Sales $t-1$	Market cap. t	Firm age (years)	Genetic Alg.	Random
Mean	−0.010	−0.008	−0.009	−0.006	−0.003	−0.004	−0.006	−0.009	−0.003	−0.006
p-value [a]	0.338	0.336	0.332	0.538	0.720	0.660	0.528	0.358	0.542	0.504
Median	−0.005	−0.003	−0.002	−0.001	0.003	0.001	0.000	−0.011	0.000	−0.012
p-value [b]	0.317	0.218	0.421	0.849	0.871	0.952	0.626	0.213	0.977	0.182
St. dev.	0.146	0.115	0.132	0.131	0.132	0.133	0.130	0.134	0.060	0.135
Min	−0.732	−0.638	−0.792	−0.625	−0.630	−0.659	−0.630	−0.607	−0.320	−0.640
Max	0.789	0.592	0.518	0.566	0.577	0.649	0.596	0.694	0.175	0.711

[a] One sample t-test.
[b] Wilcoxon signed rank test.

the genetic algorithm grouping method and the other grouping methods becomes much clearer. With simulated earnings management equaling ±2% of lagged total assets, the detection rate for the genetic algorithm grouping method is 29.0% whereas the grouping method with the second best detection rate is much lower at 12.0%. At the highest level of simulated earnings management, the detection rate for the genetic algorithm grouping method is over 90%. At this level of simulated earnings management the detection rate for the other grouping methods ranges between 29.4% and 44.0%.

To assess the overall detection rate for the grouping methods, an effectiveness score is calculated by first dividing the detection rate for the grouping method at a specific level of earnings management with the maximum detection rate at that level of earnings management. This results in 10 effectiveness scores for each grouping method. The overall effectiveness score is then calculated by averaging these 10 effectiveness scores. As the genetic algorithm grouping method has the highest detection rate at all levels of simulated earnings management, the effectiveness score for this method equals 100%. The method with the second highest effectiveness score is the two-digit SIC grouping method whereas the random grouping method shows the lowest effectiveness score.

The detection rates for the revenue/bad-debt manipulation are presented in Table 6. In general, the detection rates for the simulated revenue/bad-debt manipulation are similar to the detection rates for the simulated expense manipulation. It is mainly at the highest level of the simulated earnings management that the detection rates are somewhat higher for the simulated expense manipulation. As with the expense manipulation, the genetic algorithm grouping method clearly shows the highest detection rates for revenue/bad-debt manipulation. The second best grouping method is again the two-digit SIC grouping and the lowest performing grouping method is the random grouping.

5.3. Discussion

The results in this study provide strong evidence that the cross-sectional Jones-model with the companies grouped using a

Table 5
Expense manipulation.

Level of accrual management [a]	All (%)	Two-digit SIC (%)	Total assets t (%)	Total assets $t-1$ (%)	Sales t (%)	Sales $t-1$ (%)	Market cap. (%)	Firm age (years) (%)	Genetic Alg. (%)	Random (%)
−5%	28.6	44.0	34.2	37.8	37.0	33.0	34.0	34.2	95.4	35.4
−4%	19.0	31.8	25.2	27.2	23.4	21.4	24.6	24.6	80.6	25.0
−3%	14.2	21.0	16.4	18.8	13.0	14.8	15.0	16.0	55.2	15.2
−2%	9.8	14.2	8.4	11.8	9.4	9.4	10.2	11.6	28.6	7.8
−1%	8.4	8.0	6.0	7.6	6.0	6.4	7.6	7.2	9.2	5.4
0%	7.8	7.4	4.6	6.4	6.0	4.8	6.4	6.6	4.6	4.4
1%	8.2	7.6	4.8	6.4	6.8	6.2	8.0	7.2	12.0	4.2
2%	11.2	11.6	7.8	9.0	10.0	9.0	12.0	9.2	29.0	7.6
3%	13.6	19.6	12.6	16.2	14.8	15.6	17.8	13.2	56.8	12.8
4%	19.8	29.4	23.2	25.2	24.2	25.0	27.2	21.0	81.4	21.6
5%	29.4	43.0	36.6	35.2	37.2	39.4	37.8	33.2	93.8	32.2
Effectiveness score (%)	39.1	48.0	34.8	41.3	37.6	37.3	42.5	39.0	100.0	32.6

[a] The level of accrual management is measured as the percentage of lagged total assets.

Table 6
Revenue/bad-debt manipulation.

Level of accrual management [a]	All (%)	Two-digit SIC (%)	Total assets t (%)	Total assets $t-1$ (%)	Sales t (%)	Sales $t-1$	Market cap. (%)	Firm age (years) (%)	Genetic algorithm (%)	Random (%)
−5%	23.2	37.4	32.2	34.4	31.2	28.8	29.4	31.4	95.0	32.2
−4%	16.6	25.0	24.0	23.0	18.8	19.2	20.8	21.4	81.8	22.4
−3%	14.0	16.8	15.2	17.6	11.4	13.4	13.2	15.2	57.0	13.2
−2%	9.4	12.4	8.0	10.6	8.6	9.0	9.6	11.0	30.2	7.8
−1%	8.2	7.4	5.6	7.0	5.8	6.2	7.0	6.8	9.8	5.4
0%	7.8	7.4	4.6	6.4	6.0	4.8	6.4	6.6	4.6	4.4
1%	8.4	7.6	5.0	6.6	6.6	5.8	7.6	7.2	12.4	4.0
2%	10.6	11.0	7.2	8.6	9.6	8.6	11.0	8.8	31.0	7.2
3%	12.6	15.4	12.4	13.8	13.6	14.0	16.2	11.6	58.4	12.4
4%	16.8	23.8	21.2	23.0	21.4	23.2	23.8	18.6	84.0	19.4
5%	24.4	34.6	33.2	31.4	32.8	34.2	34.4	28.6	93.8	29.2
Effectiveness score (%)	35.4	40.4	31.9	36.7	33.1	33.3	37.2	35.1	100.0	29.6

[a] The level of accrual management is measured as the percentage of lagged total assets.

grouping genetic algorithm outperforms the cross-sectional Jones-model with the companies grouped with alternative methods. First, the standard deviation of the discretionary accruals using the genetic algorithm grouping method is less than half of the standard deviation obtained with the other grouping methods. Second, the genetic algorithm method shows significantly higher earnings management detection rates on various levels of simulated expense and revenue/bad-debt manipulation compared with the other grouping methods. At a 5% level of simulated earnings management the genetic algorithm method has a detection rate above 90%, whereas the rest of the methods have detection rates around 30%.

There are a few caveats with the grouping genetic algorithm used in this study. First, the number of groups in the grouping genetic algorithm approach is constrained to ten. It is possible that the results would have improved if a variable number of groups would have been allowed. Second, the parameters for the genetic algorithm were heuristically set as there are no clear rules for the setting of the parameters. A number of parameter combinations were evaluated but range of the parameters was rather limited. Extending the range of the parameters evaluated could result in a combination of parameters that would improve the performance of the genetic algorithm.

6. Conclusion

The purpose of this study was to assess the performance of the cross-sectional Jones accrual model when the data set firms are grouped using a grouping genetic algorithm. The results provide strong evidence that the grouping genetic algorithm method outperforms the various alternative grouping methods. This is especially clear when evaluating the earnings management detection power at different levels of simulated earnings management. The results also show that alternative grouping methods, such as the frequently used two-digit SIC grouping, perform only marginally better compared with a random grouping approach. This study could be extended by including various modifications of the Jones-model as some studies have shown that there is a difference in performance between different versions of the Jones-model. Furthermore, a wider range of settings for the genetic algorithm could be assessed. Especially, lifting the constraint of a fixed number of groups could improve the performance of the genetic grouping algorithm approach.

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