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FALSE FINANCIAL STATEMENTS: CHARACTERISTICS OF CHINA'S LISTED COMPANIES AND CART DETECTING APPROACH*

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False Financial Statements (FFS) have long been a serious problem in China and other Asian countries, which significantly dampen the confidence of the investors. Regardless of listed companies or non-listed companies, the percentage of financial statements that contained false information is quite high, which is one of the major reasons why China stock markets moved in the opposite direction towards its wonderful economic growth over the past few years. The objective of this research is to introduce one statistical technique — Classification and Regression Tree (CART), to identify and predict the impacts of FFS. We survey financial statements manipulation tricks, FFS indicators and FFS detection techniques from both China and international perspective, and further look into ten listed companies with known FFS history in China; combining these findings, we propose key indicators to work with CART.

Our analysis includes 24 false financial reports, and 124 non-false financial reports. We use CART to develop two FFS detecting models: CART without industry benchmark and CART with industry benchmark. For supporting comparison, we also build a Logit regression which is a commonly used technique in FFS detecting. We find that CART is effective in distinguishing FFS from non-FFS. Both CART models achieve better accuracy in identifying fraud cases and making predictions than Logit regression does, and CART with industry benchmark is slightly better than CART without benchmark, but it does not always have superior performance. Our CART model also tries to capture

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the indicators and their combinations that could reflect firms with high possibility of FFS in China.

Keywords: False financial statements; China's listed companies; classification and regression tree; industry benchmark.

1. Introduction

Management frauds often cause business failure such as huge loss or even bankruptcy. It can be defined as "deliberate fraud committed by management that injures investors and creditors through misleading financial statements".[6] Management fraud exists in many forms, including insider trading, creative accounting, fraudulent statements, tunneling, etc. In this research, we focus on one type of management frauds, namely falsified financial statements or fraudulent financial statements (FFS). According to the Treadway Commission, FFS are defined as intentional or reckless conducts, that result in materially misleading financial statements.[26]

FFS have become a serious concern worldwide over the past few years. Triggered by the incidence of Enron and WorldCom, US investors started to lose confidence in the US corporate governance and public disclosure, and US regulatory bodies were forced to enact a number of new regulations — including the changing duties and responsibilities of corporate board members, external auditors, senior managements, etc. — to restore investors' confidence.[3] In a developing economy like China's economy, where robust corporate governance is not well developed, problems like this are inevitable.

Some people criticized that financial statements of China's firms were generally lack of trustworthiness, and it might be the case. From March 1999 to December 2001, the Ministry of Finance (MOF) organized several investigations on financial information disclosure, and the result is astonishing:

- According to inspection bulletin No. 5 (10th July 2001), among 159 investigated firms, 147 provided untrue total assets, 155 provided untrue shareholders' equities, and 157 provided untrue incomes. The proportion of falsified amount comprised 0.95%, 1.82% and 33.4%, respectively.
- According to inspection bulletin No. 7 (12th December 2001), among 320 investigated organizations, 160 were reported to be with more than 1% of false assets and 183 were reported to be with more than 10% of false income. Aggregated falsified amount of total asset was RMB 7.38 billion, and aggregated falsified amount for income was RMB 3.51 billion. However, it might be just "the tip of the big iceberg".

The National Auditing Office also inspected 32 auditing reports provided by 16 auditing firms in 2001, it was found that 14 companies (including 41 chartered accountants) provided 23 auditing reports with serious inconsistent opinions, and the total amount of fabricated figures came up to RMB 7.1 billion, again, it might be just "the tip of the iceberg". There were no more than 100 accounting scandal cases officially recorded by China Securities Regulation Commission (CSRC) during the last 10 years, but the total fraud cases might be higher than 10,000, which means the chance of "caught and punishment" is less than 1%. Some people criticized that loose supervision and a lenient punishment mechanism toward accounting professionals in China was the reason for the problem. Other people argued that it was due to lack of accounting control or accountability structure, low corporate transparency and high opportunity for insiders-control.[19] A survey done by Hong Kong Corporate Governance Council in January 2003 summarized seven major problems affecting credibility of China's firms: (1) Insider control and concentration of power; (2) Low business ethical standard and lack of proper corporate culture; (3) Lack of independent board and effective control; (4) Lack of incentives and mature labor market for selecting executives; (5) Weak regulatory enforcement; (6) Low corporate transparency and disclosure quality and (7) Shortage of independent and qualified auditors and other intermediaries. These reasons provided a quite clear picture of why investors could not trust the financial statements disclosed by China's firms.

The outcome of such a high percentage of FFS, inadequate and ineffective supervision, poor corporate governance, etc., was the plunging of the China stock market over the past four years. FFS are also bothering China's banking industry. With high percentage of FFS, it is hard for commercial banks to build their internal credit rating systems. There are a few literatures dealing with credit scoring techniques using Chinese data (see Refs. 11, 21 and 22), but few works on credit rating have been published as "clear data" were not available.

In this paper, we try to investigate the main financial factors in China's FFS cases, and find an effective approach to detect FFS, which aims at classify the "good" and "bad" firms. First, we survey financial statements manipulation tricks, FFS indicators and FFS detecting techniques from both domestic and international literatures. By combining these considerations, we propose a set of financial factors to serve the classification purpose, because qualitative factors can hardly be accessed and are not feasible to be collected for the moment. Second, we look into ten listed companies with known FFS history in China and summarized their motivation and behavior in making FFS. For each of the tricks, we look at what financial data can be extracted to represent the trick. We expect the factor selection process should be quite close to that used in auditing practice. Third, we employ Classification and Regression Tree (CART), which is one of statistical techniques applied to support classification with wide application in medical research and credit application process but not yet used by auditing practitioners, in detecting FFS and measuring the seriousness of the data manipulation.

The paper is organized as follows: Section 2 reviews related studies in financial statement manipulation and false financial statement detection, Sec. 3 introduces our research methodology and design, Sec. 4 presents the analysis results and discussions over the findings of this research, and Sec. 5 summarizes this paper with conclusions and future researches.

2. Previous Research

2.1. *Financial statements manipulation tricks*

Financial scandals and financial statement frauds have long been a major concern to the investors worldwide. The techniques associated with the production of FFS have been discussed in Schilit's book "Financial Shenanigans".[12] The book reported seven common tricks: (1) Recording revenue before it is earned; (2) Creating fictitious revenue; (3) Boosting profits with non-recurring transactions; (4) Shifting current expenses to a later period; (5) Failing to record or disclose liabilities; (6) Shifting current income to a later period and (7) Shifting future expenses to an earlier period. The first five tricks aim at boosting current year earnings, and the last two shift current-year earnings to the future in order to create an illusion of steady income over years.

Together with merge and acquisition (M&A) and advanced financial products, such as holding derivatives or other off-balance activities, financial accounting became more and more complex, making FFS detection more difficult than ever. For example, Enron used an accounting method known as "mark to market" (MTM), in which the price or value of a security is recorded on a daily basis to calculate profits and losses. Such a method allowed Enron to project earnings from long-term energy contracts to current income. However, such earnings could not be realized for many years. With this approach, Enron managed to inflate its revenue while keeping taxable cash at a low level. On the other hand, by buying new ventures and forming off balance sheet entities, Enron moved debt off its balance sheet and transferred risk to other business ventures. These special purpose entities (SPEs) were established so that Enron was able to hide the risks or losses of its investments to produce untrue performance that pushed the company's stock. Investors believed that the stock would remain high under such an outstanding performance in the long-term, but not knowing that the losses were hidden in these SPEs. Such arrangement was extremely complex and extremely experienced auditors and lawyers could only tell which was legal and which was not.

As China's accounting system is transformed from the planned-economy accounting to the market-economy and international oriented accounting, many companies take this opportunity to improve their performance by creative accounting or even FFS. As summarized by C. Fei,[7] following tricks make FFS detection more difficult for firms in China than in western countries:

(i) *Related party transactions*: companies may move large amount of deficit into their related parties and disguise their real performance. Qiong Minyuan — one of the largest financial scandal cases in China, used related party transactions and boosted its income by 540 million.

(ii) *Non-monetary and special transactions*: non-monetary transactions, such as setting the transfer of land ownership and/or stock ownership as income, but it does not create any cash-flow. Actually, profits obtained from these operations were highly sensitive to manipulations.

(iii) *Assets restructuring*: assets restructuring has many positive impacts when the company expends. However, some companies take it as a means of *financial statement restructuring* or *performance enhancement*. The accounting process involved in is very complicated, and it is difficult for auditors to discover such frauds.
(iv) *Change of accounting estimates*: Chinese accounting principle allows companies to change their accounting estimates if necessary. Some companies take it as a means to manipulate income. Typically, it is achieved by changing the method of estimating long-term investments and adjusting the area of consolidation.

Therefore, traditional auditing might be insufficient to discover the FFS, and additional analytical procedures should be included for this purpose.

2.2. *FFS indicators*

A number of studies have been conducted on the fundamental side to design indicators for FFS. A report by the Committee of Sponsoring Organizations of the Treadway Commission (COSO) examined fraudulent financial reporting from US public companies covering the period 1987–1997, and some critical insights include:

(i) The companies committing fraud generally were small;
(ii) In 72% of the cases CEO appeared to be associated with the fraud, and in 43% of the cases CEO were associated with FFS;
(iii) The audit committees were weak, and the companies' board of directors were dominated by insiders;
(iv) The founders and board members owned a significant portion of the companies;
(v) Serious consequences resulted when companies committed fraud, including bankruptcy, significant changes in ownership, and/or other serious punishments.

In 1997, the American Institute of Certified Public Accounts (AICPA) issued Statement of Auditing Standards (SAS) No. 82: *Consideration of Fraud in a Financial Statement Audit*. This statement discussed risk factors, or *red flags* that relate to fraudulent financial reporting. The signals were grouped into three categories, namely *management's characteristics and influence over the control environment*, *industry conditions*, and *operating characteristics and financial stability*. Risk factors associated with *Management's characteristics and influence over the control environment* include: (1) A significant portion of management's compensation is represented by bonuses, which is contingent upon the entity's operating results or financial position; (2) An excessive interest by management in maintaining or increasing the entity's stock price or earning trend through aggressive accounting practices; (3) An interest by management in pursuing inappropriate means to minimize reported earnings for tax-motivated reasons; (4) Domination of management by a single person or small group without compensating controls such as effective oversight by the board of directors or audit committee; (5) Inadequate monitoring on significant controls; (6) Management setting aggressive financial target and expectations for operating personnel; (7) Management continuing to employ an ineffective accounting, information technology or internal auditing staff; (8) High turnover of senior management, counsel, or board members; (9) Known history of securities law violations and (10) Switching CPA and/or conducting asset re-evaluation for unknown reasons.

Risk factors associated with *Industry conditions* include: (1) New accounting or regulatory requirements that could impair the financial stability or profitability of the entity; (2) High degree of competition or market saturation, accompanied by declining margins; (3) Declining industry with increasing business failures and significant declines in customer demand and (4) Rapid changes in the industry, such as high vulnerability to rapidly changing technology or rapid product obsolescence.

Risk factors associated with *Operating characteristics and financial stability* include: (1) Significant pressure to obtain additional capital necessary to stay competitive considering the financial position and (2) Assets, liabilities, revenues, or expenses based on significant estimates that involve unusually subjective judgments or uncertainties, or that are subject to potential significant change in the near term in a manner that may have a financially disruptive effect on the entity, such as ultimate collectability of receivables, timing of revenue recognition, realizability of financial instruments based on the highly subjective valuation of collateral, difficult-to-assess repayment sources or significant deferral of costs.

Similar studies have conducted in China. An article[8] indicated that four types of companies are most prone to managerial scandals:

(i) *Companies with frequent capital operations and related-party transactions*: most of these operations were fabricated.
(ii) *Companies with high- and volatile-stock prices*: the illusion was typically created by market makers and the performance was just a lie.
(iii) *Initial Public Offering* (*IPO*) *companies*: they were usually restructured before listing, and performance reported in the prospectus was typically far too good from their capabilities.
(iv) *Companies in a declining or over-competitive business environment*: these companies usually had poor actual performance. However, they employed accounting tricks to create stable income over a few years, and then they simply announced a big drop in performance and quit the market with all the capital.

Generally speaking, China has few new tricks of FFS compared with the western world, but the degree of FSS is much higher than that in the western world, due to the immature legal system and the eager-for-rich social psychology in the transition period. For example, Hubei Lantian Co. Ltd. fabricated its accounting books from the very beginning (its IPO) to the end (its FSS were discovered), almost everything in their financial reports was false.

2.3. *FFS detection*

There are a few literatures working on introducing advanced techniques or constructing formal models to detect FFS. Beasley[1] used Logit regression to test the prediction that the inclusion of larger proportions of outside members on the board of directors significantly reduces the likelihood of financial statement fraud with a sample of 150 American firms. They found that non-fraud firms have boards with significantly higher percentages of outside members than fraud firms. Additionally, as outside director ownership in the firm and outside director tenure on the board increased, the number of outside directorships in other firms held by outside directors decreased, the likelihood of financial statement fraud decreased.

Fanning *et al.*[15] introduced Artificial Neural Networks (ANN) to predict management fraud. Their study examined a wide variety of variables covering both quantitative (such as financial ratios, financial accounts and trends) and qualitative information (such as corporate governance, auditor, agency issues, subsidiaries, personnel, litigation, etc.). The analysis through AutoNet (one of ANN implementations) with a sample of 204 American firms found 20 variables to be possible indicators of FFS, where seven were associated with financial ratios. It is found that FFS were associated with higher accounts receivable to sales, higher inventory to sales, lower net property plant and equipment to total assets, higher debt to equity, lower Z-score, lower sales to total assets, and higher accounts receivable growth rate.

Spathis[24] employed stepwise logistic regression to construct a FFS detection model for companies in Greece. By a sample of 76 Greek firms, his study indicated that debt to equity, sales to total assets, inventory to sales, total debt to total assets, and financial distress (Z-score) were helpful financial ratios to discriminate false from non-false financial statements. Fraudulent financial statements were usually associated with higher debt to equity, lower sales to total assets, higher inventory to sales, higher total debt to total assets, and lower Z-score than non-fraud ones.

A common feature of above studies is regarding the FFS detection problem as an instance of *classification and decision problems*, where characteristics of both false and non-false cases are collected, and a classification rule that best discriminates the false and non-false cases is developed. In this research, we apply the same idea. CART is chosen as the classification methodology and we aim at testing its effectiveness.

3. Methodology and Stylized Facts of Sample

In this section, we first introduce the methodology used in this research — CART. Then, we briefly discuss the list of firms to be included in our study. Finally, we present a summary of FFS tricks used by these firms, as well as our choice of variables and sample accordingly.

3.1. *CART*

CART is a computerized, non-parametric technique different from traditional statistical methods. CART has been applied in the area of medical decision making,[10] commercial loan classification,[16] and prediction of financial distress.[9] CART applies the binary Recursive Partitioning Algorithm (RPA) to best classify samples into a number of non-overlapping regions, each of which corresponds to a terminal node in the tree, CART then assigns each terminal node into one of the classes based on the criteria of minimizing expected misclassification costs. The expected cost of misclassifying a class i object into class j, or the misclassification risk at a terminal node t is defined as:

$$R_j(t) = c_{ij}p(i,t) = c_{ij}\pi_i p(t|i) = c_{ij}\pi_i n_i(t)/N_i, \tag{3.1}$$

where c_{ij} is the cost of misclassifying a class i observation into class j, π_i is the prior probability of an observation belonging to class i, $n_i(t)$ is the number of observations from class i a terminal node t and N_i is the total number of observations belonging to class i. The terminal node t is then assigned to a class corresponding to the minimum risk. The risk of the entire tree T, denoted by $R(T)$, is the sum of risks of its terminal nodes. A special case exists when misclassification costs all equal to 1, and the prior probability is the original sample proportion, then the minimum risk rule implies each terminal node is assigned to a class which has majority representation in this node, and the risk of the tree is simply the overall misclassification rates.

The tree construction process comprises two phases: *growing* and *pruning*. In the growing phase, RPA is applied to divide the samples into a number of non-overlapping regions. In each iteration, CART seeks the best splitting variable which minimized expected misclassification costs to split the node into two children nodes. The misclassification cost at each node is measured by the *impurity function*:

$$I(t) = \sum_{i=1}^{k} R_i(t)p(i|t), \tag{3.2}$$

where $p(i|t)$ is the conditional probability that an observation in node t is assigned to group i; and k is the number of classes. The impurity of a tree is defined as the sum of impurities of its terminal nodes. Once a terminal node t is further split into two children nodes, t_L and t_R, the decrease in the impurity of the tree is:

$$\Delta I(t) = I(t) - (I(t_L) + I(t_R)), \tag{3.3}$$

where $\Delta I(t)$ is nonnegative and its magnitude depends on the choice of the split. The best split for the current terminal node t expects $(I(t_L) + I(t_R))$ to be minimized, which allows the split to maximize $\Delta I(t)$. The best splitting variable could be found by an exhaustive search of all possibilities, but efficient algorithms have been developed to improve the efficiency (see Ref. 30). The growing phase stops when one of the following conditions is satisfied: (1) there is only one observation in each child node; (2) no further splitting is able to decrease the impurity of the current tree and (3) an external limit on the depth of the tree is reached.

The pruning phase aims at selecting the correct complexity of the tree. The minimal misclassification cost tree obtains from the growing phase usually overfits the data because it is constructed solely with respect to the samples, which is not necessarily represents the population characteristics. Pruning is conducted according to the *cost-complexity* criteria. The cost-complexity for each sub-tree of the optimal tree is:

$$CC = R(T) + K \text{ (number of terminal nodes of } T), \tag{3.4}$$

where $R(T)$ is the sum of misclassification rates for all terminal nodes and K is a nonnegative constant representing a *penalty* for complex trees. The pruning starts from the bottom level, and K increases gradually in the pruning process. The child nodes are pruned away if the resulting change in the predicted misclassification cost is less than K times the change in tree complexity, for example, if $(R(T') - R(T')) <$ K (number of terminal nodes of T' − number of terminal nodes of T), then the tree T' is preserved as a better solution.

The primary difference between CART and traditional statistical approaches is that the CART partitions variable space into a number of rectangular regions, while traditional statistical approaches (such as Linear Discriminant Analysis) partition the variable space into two half-spaces. Another difference is the way they deal with prior probabilities and costs of misclassification impacts: traditional statistical models are established first by group separation criteria such as maximizing inter-group to intra-group variance, and then assign observations into the corresponding group based on error costs and prior probabilities; CART, on the other hand, simultaneously determines the variable selection and group assignments with the costs and prior probabilities helping to determine the splitting. Therefore, CART is more sensitive to the training data especially when outlier exists. Moreover, the non-parametric property of CART is desirable in examining data without known distributional properties. Therefore, CART is chosen for the FFS detection in this research.

3.2. *Selected FFS firms and their tricks*

During the past twenty years, lots of listed companies in China got involved in fraudulent financial statements. In this subsection, we introduce ten most serious and well known financial scandal cases among companies listed in the A-share market in China. Their financial statement manipulation histories are presented shortly as follows:

Guangxia: Guangxia Yinchuan Industry Co. Ltd (stock code 000557, abv. Guangxia) made use of fabricated contracts, import-export reports, tax reports and bank notes and successfully created a large number of fictitious transactions. False revenue reported was RMB 526 million in 1999 and 909 million in 2000.

Lantian: Hubei Lantian Co. Ltd (stock code 600709, abv. Lantian) made a perfect series of false financial reports from 1996 to 2000. Its financial scandal was discovered in 2001 and people found that in the year of 2000 alone, the fabricated fixed assets and revenue were RMB 2.17 billion and 1.84 billion, respectively, which were twice and forty times higher than corresponding true figures.

Zhangjiajie: Zhangjiajie Tourism Development Co. Ltd (stock code 000430, abv. Zhangjiajie) applied inappropriate revenue recognition methods and significantly overstated its revenues in 1996 and 1997. The amount of overstated revenue was RMB 80 million in 1996 and 43 million in 1997. In 1998, it transferred 6 million interest income into its profit account, which boost net income by 5.28 million.

Dawn Garments: Shenyang Dawn Garments Co. Ltd (stock code 600167, abv. Dawn Garments) manipulated its financial statements in 1999 by overstating its assets of RMB 90 million, liabilities 20 million, shareholders' equities 74 million, revenue 150 million and before tax incomes 87 million, the original 34 million loss was turned into 52 million profit.

Zhengzhou Baiwen: Zhengzhou Baiwen Co. Ltd Group (stock code 6008998, abv. Zhengzhou Baiwen) used accounting tricks such as creating fictitious revenue, understating liabilities and adjusting timing of revenue recognition to beautify its performance since listed. From 1996 to 1997, accumulated manipulated income was RMB 144 million.

Dongfang Boiler: Dongfang Boiler Group Co. Ltd (stock code 600786, abv. Dongfang Boiler) shifted RMB 176 million revenue and 38 million incomes of the year 1996 into 1997. Similarly, it shifted 226 million revenue and 47 million incomes of the year 1997 into 1998. These actions created a steady growth of net assets turnover for three years.

Luoyang Chundu: Luoyang Chundu Foodstuffs Co. Ltd (stock code 000885, abv. Luoyang Chundu) failed to disclose several important related party transactions (related to an amount of RMB 431 million) in the 1999 financial reports; it also failed to record RMB 380 million expenses that year, which either affected its asset valuation or profits.

Luzhou Laojiao: Luzhou Laojiao Co. Ltd (stock code 000568, abv. Luzhou Laojiao) issued a readjustment announcement in May 2003, it was found that after the adjustment, its performance differed a lot from that reported in 2002 annual report: net income changed from RMB 51 million to 31 million, 39.92% decreased; adjusted EPS decreased from 0.0978 to 0.0588, and return on net assets decreased from 3.457% to 2.077%.

Hongguang: Chengdu Hongguang Industrial Co. Ltd (stock code 600083, abv. Hongguang) applied financial manipulation tricks such as creating fictitious sales and inventory, which turned RMB 103 million losses in 1996 annual reports into RMB 157 million profits. In its 1997 annual reports, the loss amount reported was RMB 198 million, while the true loss amount was RMB 230 million.

Dadonghai: Hainan Dadonghai Tourism Centre Holdings Co. Ltd (stock code 000613, abv. Dadonghai) used tricks such as inappropriate accounting estimates for account receivables and creating fictitious revenue repeatedly during 1993 and 1997. The total amount of fabricated income was as high as RMB 228 million.

A summary over above discussed FFS firms is presented in Table 1. It is observed that these cases came from several traditional industries, such as agriculture, tourism, retails, machinery, food, beverage, electronics and hotel. These industries are *unprotected*, which do not receive a direct supervision from the State Council. The entry barriers for these industries are relatively low, and the firms have to compete openly in the domestic market. Therefore, many companies *re-packaged* their performance in order to get the listing privilege. As observed from Table 1, seven out of the ten companies made FFS since or even before the listing time. Two companies (Lantian and Dadonghai) made FFS for five consecutive years, and others made FFS for one to three years.

Table 2 summarizes the true figures of four key financial accounts (in RMB) and percentage overstated in part of above stated FFS cases, the true figures are subtracted from financial statements of these firms disclosed in later years. It is not hard to observe that except for Luzhou Laojiao case (code 000568), all the other cases made very aggressive manipulations and the results are essential to mislead investors. For example, six out of the twelve cases overstated net income more than 100%, which turned original losses into profits. Another extreme case is Guangxia case (code 000557), where shareholders' equity was overstated by 455.08%; the company was supposed to go into bankruptcy, but accounting tricks just disguised this fact.

Table 1. Summary of FFS firms.

Company Abv.	Listing Time	Market	Industry	Year of Fraud
Guangxia	June 1994	SZ A Shr	Agriculture	1999–2000
Lantian	June 1996	SH A Shr	Agriculture	1996–2000
Zhangjiajie	August 1996	SZ A Shr	Tourism	1996–1998
Dawn Garments	January 1999	SH A Shr	Commerce	1999
Zhengzhou Baiwen	April 1996	SH A Shr	Retail	1996–1997
Dongfang Boiler	December 1996	SH A Shr	Machinery	1996–1998
Luoyang Chundu	March 1999	SZ A Shr	Food	1999
Luzhou Laojiao	May 1994	SZ A Shr	Beverage	2002
Hongguang	June 1997	SH A Shr	Electronics	1996–1997
Dadonghai	January 1997	SZ A Shr	Hotel	1993–1997

Table 2. True financial performance and percentage manipulated.

Stock Code (Year)	Revenue (Percent Overstated)	Net Income (Percent Overstated)	Total Assets (Percent Overstated)	Shareholders' Equity (Percent Overstated)
000557 (99)	383,579,946.11 (37.14)	127,786,600.85 (0.00)	2,191,828,506.7 (10.86)	942,460,049.35 (0.00)
000557 (00)	130,261,227.08 (507.82)	−135,823,810.33 (407.49)	1,429,597,831.2 (120.43)	−340,353,948.53 (455.08)
600709 (00)	38,094,774.28 (4732.45)	−10,686,569.22 (4238.98)	1,155,472,867.8 (145.58)	129,253,932.45 (1585.38)
600709 (99)	24,238,787.13 (7538.29)	−22,879,728.64 (2342.28)	874,766,383.2 (167.27)	268,102,569.94 (551.54)
000430 (98)	51,881,314.46 (57.56)	−3,026,424.63 (971.37)	382,818,289.09 (−21.5)	194,558,190.8 (12.46)
000430 (97)	74,637,404.09 (0.00)	16,803,355.77 (25.54)	255,765,602.19 (1.68)	187,774,926.74 (2.29)
600167 (99)	256,654,941.65 (59.52)	−22,092,554.43 (260.27)	722,999,232.86 (13.09)	486,935,263.07 (15.22)
600786 (98)	930,774,189.34 (0.00)	−12,615,680.52 (114.36)	1,736,772,532.62 (3.14)	486,447,331.89 (11.02)
600786 (97)	1,099,603,666.53 (0.00)	11,272,484.23 (131.20)	1,859,447,299.39 (0.80)	519,975,695.46 (2.84)
000885 (99)	455,777,719.99 (0.00)	11,900,880.05 (102.34)	956,159,003.71 (1.27)	622,859,690.49 (1.96)
000568 (02)	1,044,804,516.22 (0.00)	30,561,457.09 (1.10)	2,466,806,230.09 (0.00)	1,497,344,371.69 (0.02)
600083 (97)	270,659,389.93 (0.00)	−229,221,127.45 (13.45)	1,798,121,329.88 (5.98)	611,509,264.47 (18.41)

3.3. *Summary of FFS tricks and choice of variables*

As observed from above cases, nearly all of fraudulent actions occurred in transactions within the revenue cycle. A flowchart of FFS production is illustrated in Fig. 1. The primary aim of these FFS firms was to overstate their revenue and income, so as to disguise losses and avoid punishment from the regulatory bodies. Most firms above boosted their revenue by creating fictitious transactions. Therefore, the following four variables are included to examine the possibility of revenue overstatement:

- R1 — The ratio of revenue to total assets;
- R2 — The ratio of current liabilities to revenue;
- R3 — The ratio of total liabilities to revenue and
- R4 — Absolute value of percentage of one-year revenue change.

Overstating revenue would jointly raise account receivables and/or cash (or the other way round), as income is the primary source of shareholders' equity, both income and shareholders' equity can be exaggerated. Sometimes firms choose to understate expenses instead of overstate revenues, as understating expenses would

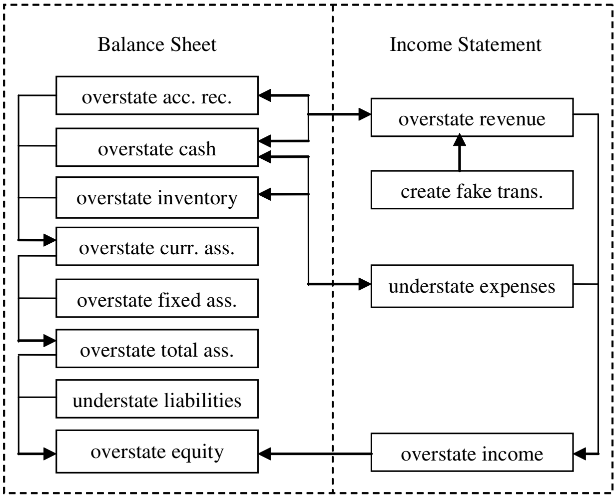

Fig. 1. Flowchart of FFS production.

jointly raise cash and/or inventory (or the other way round), the effect is just equivalent. Therefore, the following variables are added in our examination:

- R5 — Net income as percentage of revenue;
- R6 — Net income as percentage of total assets;
- R7 — Absolute value of percentage of one-year net income change;
- R8 — Account receivable as percentage of revenue;
- R9 — Account receivable as percentage of current assets;
- R10 — Absolute value of percentage of one-year account receivable change;
- R11 — Inventory as percentage of revenue;
- R12 — Inventory as percentage of current assets;
- R13 — Absolute value of percentage of one-year inventory change;
- R14 — Cash as percentage of revenue;
- R15 — Cash as percentage of current assets;
- R16 — Absolute value of percentage of one-year cash change;
- R17 — Operating expense as percentage of revenue;
- R18 — Selling and administrative expense as percentage of revenue;
- R19 — Financial expense as percentage of revenue;
- R20 — Retained earnings as percentage of total assets and
- R21 — Retained earnings as percentage of shareholders' equity.

Firms making FFS were also interested in assets manipulation, because a strong assets position would be more attractive for investors. Assets manipulations are typically done through overstating inventory and fixed assets using inappropriate depreciation methods and other accounting estimates; overstating account receivables and cash to boost revenue or as a result of revenue manipulation; overstating assets and understating liabilities by intentionally re-classify accounting items, omitting debts, and other fabrication tricks. Therefore, three more variables are added to our analysis:

- R22 — Fixed assets as percentage of total assets;
- R23 — Absolute value of percentage of one-year fixed assets change and
- R24 — Absolute value of one-year fixed assets depreciation as percentage of fixed assets change.

4. Experiments and Discussions

In this section, we build two CART models, CART without industry benchmark (vertical analysis) and CART with industry benchmark (horizontal analysis). The former is to apply CART directly on the original data, while the latter is to use the data adjusted by industry benchmark. It is intuitive that horizontal analysis may be more effective than vertical analysis in catching such FFS. The reason is that some companies were able to manipulate their financial statements for several years, therefore it was not easy to trace the vertical trend to detect the existence of these falsified financial data. However, industry benchmark is difficult to manipulate and it is also a public data. Therefore, horizontal analysis provides a reference point to support CART's classification. To judge our models, we also build a Logit regression model for comparison.

The data set for the empirical experiments consists of 148 financial reports. Financial data for the FFS cases are extracted from CSMAR annual report database, we are able to form the FFS group with 24 false financial reports (data for Dadonghai 93 is not available). The non-FFS group is formed by searching other available financial reports matched against the industry and the year to the FFS examples, we eliminate those reports with incomplete data and 124 financial reports are included in the non-FFS group. An inherent limitation in this study is the inability to identify whether fraudulent acts occurred in the non-FFS group; it only guarantees that there was *no public available information* indicating those financial reports to be falsified.

4.1. *CART without industry benchmark*

The CART analysis aims at finding out patterns associated with FFS among China's firms, so that fraud cases can be identified efficiently. The result of CART analysis is illustrated in Fig. 2. The terminal nodes are represented by rectangles. Four terminal nodes correspond to *high probability of FFS* (HPFFS) and two correspond to *low probability of FFS* (LPFFS). The figure $(x : y)$ at each node represents the number of FFS cases to non-FFS cases, for example, $(24 : 124)$ at the root node means there are 24 FFS cases and 124 non-FFS cases initially. We define type I

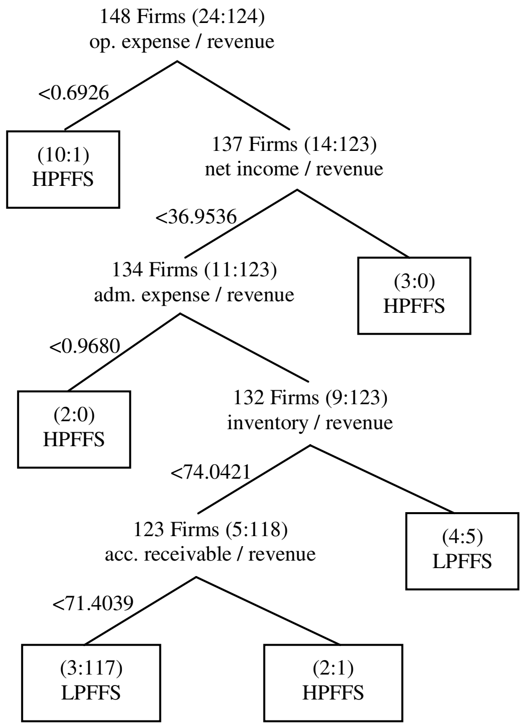

Fig. 2. Output of CART without industry benchmarking.

misclassification as classifying an FFS case into non-FFS, and type II misclassification vice versa. We initiate the cost of type I misclassification to be 1, and the cost of type II misclassification to be 0.5, the total misclassification cost is 0.0541, where type I misclassification rate is 29.167% and type II misclassification rate is 1.613%.

The CART analysis selected five variables, namely operating expenses as percentage of revenue (R17), net income as percentage of revenue (R5), selling and administrative expense as percentage of revenue (R18), inventory as percentage of revenue (R11), and account receivables as percentage of revenue (R8). As observed from this analysis, firms with operating expenses less than 0.6926% of revenue are highly suspicious for FFS. As a result, ten out of 24 FFS cases are identified by this single indicator. Firms with net income larger than 36.9536% of revenue, selling and administrative expenses less than 0.9680% of revenue, and account receivables larger than 71.4039% of revenue are also high suspicious for FFS.

4.2. *CART with industry benchmark*

Now let us turn to CART with industry benchmark. For CART with industry benchmark, instead of using the data directly, each data item is subtracted by

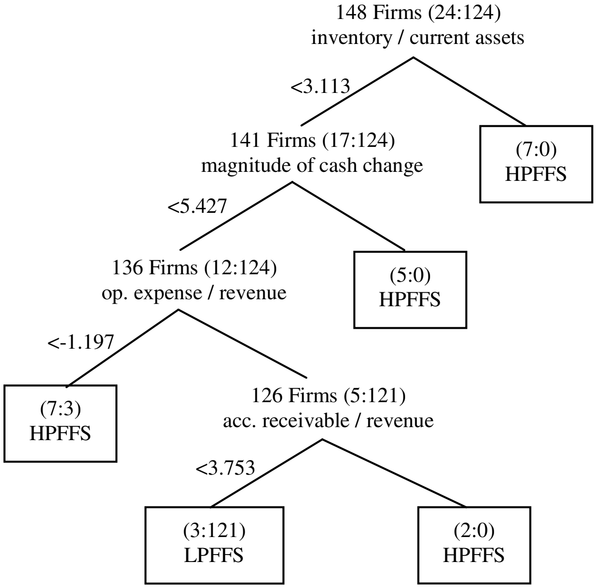

Fig. 3. Output of CART with industry benchmarking.

corresponding industry the mean value divided by industry standard deviation, so that each variable is converted to a vector of *standard scores*. The result is illustrated in Fig. 3. With the same settings, the total misclassification cost is 0.0304, where type I misclassification rate is 12.5% and type II misclassification rate is 2.42%.

There are four variables involved in the CART analysis, namely inventory as percentage of current assets (R12), magnitude of one-year cash change (R16), operating expense as percentage of revenue (R17), and account receivables as percentage of revenue (R8). As observed from this analysis, firms with inventory as percentage of current assets higher than 3.113 standard deviations, magnitude of one-year cash change larger than 5.427 standard deviations and operating expense as percentage of revenue lower than -1.197 standard deviations compared with industry average are highly suspicious for FFS. As a result, 19 out of the 24 FFS cases are identified by these characteristics. Moreover, firms with account receivables as percentage of revenue higher than 3.753 standard deviations comparing with industry average are also highly suspicious for FFS. In fact, this result just proves that FFS companies are likely to overstate inventories, account receivables, revenue and understate expenses. The cash account is also likely to be manipulated so that FFS cases have more volatile cash change than non-FFS cases.

4.3. *Logit regression*

Logit regression has been a popular approach in previous FFS studies; it is also a widely used approach in researches related to finance and social science. In this

Table 3. Result of Logit analysis.

Ratios	Without Industry Benchmarking		With Industry Benchmarking	
	Coefficient	p-Value	Coefficient	p-Value
Constant	−11.4660	(0.0043)**	−4.8562	(0.0000)**
R1	1.1815	(0.3089)	1.6318	(0.0256)**
R2	−8.4474	(0.0102)**	−1.3537	(0.4248)
R3	6.1027	(0.0152)**	2.2781	(0.1082)
R4	0.0078	(0.1068)	0.7057	(0.0929)
R5	0.0409	(0.4479)	0.6132	(0.5961)
R6	0.0621	(0.6921)	−2.1823	(0.0232)**
R7	−0.0031	(0.3021)	0.9693	(0.0079)**
R8	0.0332	(0.3165)	−0.4798	(0.6071)
R9	0.1309	(0.0321)**	2.1678	(0.0149)**
R10	−0.0002	(0.6809)	−0.2176	(0.6587)
R11	−0.0046	(0.8547)	0.1837	(0.6423)
R12	0.0917	(0.0338)**	1.6360	(0.0029)**
R13	0.0029	(0.0659)	0.0971	(0.7535)
R14	−0.0098	(0.7348)	1.3271	(0.0631)
R15	0.1157	(0.0158)**	0.2280	(0.7908)
R16	0.0007	(0.6421)	0.1807	(0.0000)**
R17	0.1613	(0.0177)**	−0.2125	(0.0944)
R18	−0.0646	(0.6025)	0.5542	(0.5318)
R19	0.5913	(0.0237)**	−1.2828	(0.1523)
R20	0.0233	(0.7922)	1.6811	(0.1396)
R21	0.0302	(0.0919)	0.6022	(0.4499)
R22	−0.0243	(0.4448)	0.5133	(0.3293)
R23	0.0030	(0.2519)	0.1291	(0.3567)
R24	−0.0872	(0.0644)	0.1160	(0.0178)**

**Variable significant at 95% confidence level.

subsection, we use Logit regression as a benchmark to test the performance of our proposed approach. The result of Logit regression is illustrated in Table 3, where variables significant at 95% confidence level were marked by double-stars.

The Logit analysis indicates that FFS in China's firms are associated with higher account receivables in percentage of current assets, higher inventory in percentage of current assets, higher operating expenses in percentage of revenue, higher financial expenses in percentage of revenue, higher total liabilities to revenue and lower current liabilities to revenue. The first two observations provide evidence on account receivable manipulation and inventory manipulation, the following three observations indicate that FFS firms typically have worse operating performance and more difficult financial position. Compared with the results of CART analysis, similar phenomenon can be explained, but the variables are chosen differently. The major reason is that Logit regression and CART used different classification criteria: Logit regression aims at maximizing the likelihood function while CART aims at minimizing the total misclassification cost. Another reason is that financial manipulation tricks were applied in different ways and different extents in the sample FFS cases,

Table 4. Comparing misclassification rates of CART and Logit regression.

	CART		Logit Regression	
	No Benchmarking	Benchmarking	No Benchmarking	Benchmarking
Type I	0.2917	0.1250	0.3725	0.2083
Type II	0.0161	0.0242	0.0403	0
Overall	0.1539	0.0746	0.2064	0.1042

with a relatively small sample size, the pattern or characteristics cannot be well concluded yet.

4.4. *Discussions*

The performance of two CART experiments and Logit regression is compared in Table 4. For the original dataset, type I error of CART was 29.17% and that of Logit regression was 37.25%, type II error of CART was 1.61% and that of Logit regression was 4.03%, it is not difficult to observe that CART achieves better accuracy in predicting both the fraud case and non-fraud case with the original dataset; for the benchmarked dataset, type I error of CART was 12.5% and that of Logit regression was 20.83%, type II error of CART was 2.42% and that of Logit regression was 0, although Logit regression achieved better accuracy in predicting the non-fraud case, the error for predicting fraud case was much higher and the overall performance of CART was better (7.46% v.s. 10.42%). Auditors and financial analysts are typically concerned about any possibility of FFS, therefore, an approach with lower type I error rate will better serve this purpose. Overall, CART outperforms Logit regression in both fraud identification accuracy and overall accuracy.

It is notable that three variables play important roles in the three experiments. They are operating expense as percentage of revenue (R17), account receivables as percentage of revenue (R8), and inventory as percentage of current assets (R12). R17 and R8 appear in both CART models with and without benchmark, and R12 is not only the first factor in CART model with benchmark, but also appears significant in logit regression models with and without benchmark. An obvious observation is that the numerators in these three variables, i.e. operating expense, account receivables and inventory, are easy targets for manipulation. They are "soft" items in financial reports in comparison with "hard" items such as "sales", "retained earnings", etc. The interesting thing here is that the cheating companies fabricate "soft" items much larger than "hard" items, thus the corresponding ratios become outliers. The implication for regulators and accounting practitioners is that more attention should be pay on the "soft" items in the financial reports, and look into whether they deviate from their normal values matched to their business sizes.

In order to further examine the effectiveness of our proposed method, a Jackknife approach similar to Spathis *et al.*[25] is employed for validation. The validation is conducted in the following way: first, one FFS case and one non-FFS case are

Table 5. Comparing misclassification rates with raw data (standard deviation of the rates are put in the parentheses).

	CART				Logit Regression			
	Training Sample		Validation Sample		Training Sample		Validation Sample	
Type I	0.2097	(0.0669)	0.3167	(0.4653)	0.4128	(0.0370)	0.7187	(0.4497)
Type II	0.0256	(0.0077)	0.1028	(0.3038)	0.0406	(0.0042)	0.1174	(0.3219)
Overall	0.1177	(0.0319)	0.2098	(0.2747)	0.2267	(0.0195)	0.418	(0.2689)

Table 6. Comparing misclassification rates with benchmarked data (standard deviation of the rates are put in the parentheses).

	CART				Logit Regression			
	Training Sample		Validation Sample		Training Sample		Validation Sample	
Type I	0.1226	(0.0280)	0.4516	(0.4977)	0.2228	(0.0229)	0.5011	(0.5001)
Type II	0.0045	(0.0059)	0.0414	(0.1992)	0.0001	(0.0009)	0.0391	(0.1939)
Overall	0.0635	(0.0127)	0.2465	(0.2684)	0.0114	(0.0114)	0.2701	(0.2694)

selected to form a validation sample, and the rest cases form a training sample; second, we use the training sample obtained in the last step to develop one CART model and one Logit regression model; finally, the validation sample is tested against those two models and misclassification rates are recorded. This validation is tested against all combinations of FFS with non-FFS cases, and totally there are $24^{*}124 = 2976$ trials. The results are illustrated in Tables 5 and 6.

In our research, we find that in both datasets, CART achieves better performance in identifying the fraud cases, the overall performance is also better for the validation sample. Therefore, we conclude that CART is a more effective approach in identifying and predicting FFS for firms in China. It is also observed that industry benchmarking gives a more accurate classification in the training sample, but the misclassification rates are higher in the validation sample, therefore, industry benchmarking does not produce uniformly superior results.

5. Summary and Future Research

In this research, we present a comparison study on the FFS, international experience and China's situation. Based on the characteristics of China's FFS cases, we develop a flowchart for investigating the tricks used in financial data manipulation in China. Further, we apply CART to detect the seriousness of financial data manipulation in China financial scandal cases. We compare the performance of our proposed approach with Logit regression, and we find that CART outperforms Logit regression that it is able to produce more accurate classification on the fraud cases, and the prediction accuracy is also higher for CART. Therefore, CART can be considered as an effective approach in FFS identification and prediction, and FFS detection systems can be built based upon such model. However, financial manipulation tricks varies significantly in the sample FFS cases, with a relatively small sample size, the pattern or characteristics cannot be well concluded yet.

In future researches, a larger FFS sample is required in order to get more convincing results on patterns or characteristics of FFS firms. We will also build a decision support system to support FFS detection. In order to achieve accurate results, selecting proper industry peers and variables for comparison is important. A better data representation scheme is necessary, and such scheme should be able to describe not only the meaning of each data item, but also the interrelationship among data items. An XML-based representation would better serve this purpose. Dynamic identification of industry peers and variables require more advanced data analysis and processing techniques, and lack of qualified data is another challenge to support such analysis. Data mining may be a remedy for these problems, and more researches on this perspective will be conducted in the future.

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