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Editorial Open Access

Detecting Fraud in Accounting and Marketing

Linda L Golden[1]*, Marlene[1], Morton Meyerson[1], Patrick L Brockett[2] and Gus Wortham[2]

[1]Centennial Professor in Business and Professor of Marketing, The University of Texas-Austin, USA
[2]Chair in Risk Management, The University of Texas-Austin, USA

Fraud creates a substantial and costly drag on the national economy, as well as on firms (e.g., Enron, World Com, Arthur Anderson, regulatory compliance costs associated with Sarbanes-Oxley, etc.). According to the National Insurance Crime Bureau [1] fraud is the second most costly white collar crime in the USA (the first being tax evasion). Moreover, about 10% of all white collar crime incidents involve accounting related filing of fraudulent financial statements ([2], quoting a study by Association of Certified Fraud Examiners).

The fraud issues are not restricted to the USA as it is a world-wide phenomenon. According to a report from the accounting firm BDO LLP, the average global cost of fraud is about £2.91 trn ($4.7 trillion) amounting to almost 5.5% of global GDP. They further estimate that in the UK about £85.3 bn ($138.2 bn) is lost each year to fraud [3].

In a consumer setting, fraud perpetrated by customers can also be very costly to firms, also. For example, customer return fraud is an increasing issue for retailers [4], and the Federal Bureau of Investigation (FBI) estimates that health care fraud alone in the USA costs about $80 billion every year (FBI 2013) [5]. NICB estimates that ten percent of U.S. property and casualty insurance claims are fraudulent, with Accenture estimating that fewer than 20 percent of these fraudulent insurance claims are detected or denied (Accenture 2010) [6].

Part of the problem in detecting fraud in accounting and marketing (and a reason why such detection is difficult) is that in many situations the fraudsters are actively trying to hide their behavior. In much of marketing research we rely on observing or explicitly expecting subjects to disclose their behavior-fraud is not likely to be self-disclosed. Further, while certain types of fraud can be detected using parametric statistical models (like logistic regression) trained on a known sample of discovered fraudulent transactions there are other types of fraud for which the identification of fraudulent action is very difficult. An example of fraud that lends itself to parametric statistical analysis is credit card fraud where the fraudulent charges can be identified by the legitimate card user at the end of the billing cycle (or before) or the credit card company identifies a series of card use actions suspicious of theft.

On the other hand, fraud less visible and difficult to identify *a priori* statistically with a set of predictor variables is deceptive financial statements in accounting. Fraud can be very difficult to identify in services marketing also, such as insurance, wherein a formerly profitable customer may be the perpetrator (opportunistic fraud), or there may be a carefully designed scheme to cover the tracks of an organized premeditative fraud. Click fraud associated with pay-per-click advertising on the Internet is yet another example where separating the fraudulent click-throughs from the non-fraudulent click through (for payment purposes) may be extremely difficult [7].

While a dependent variable designating whether or not fraud has occurred may not be available for model building, there often are "red flag" indicators available that arouse suspicion of fraud or that give hints that fraud may have occurred. For example for financial statement fraud, Investopedia (2011) [2] presents a list of red flag indicators of financial statement fraud shown below.

- Accounting anomalies, like growing revenues without corresponding cash flow growth.
- Consistent sales growth in times when competitors are showing weak performance.
- An unexplainable rapid rise in the number of sales in receivables in addition to growing inventories.
- A big surge in company performance in the final reporting period of fiscal year.
- The company consistently maintains their gross profit margins whereas others in their industry are facing pricing pressure.
- A large buildup of fixed assets (which might flag their using operating expense capitalization, instead of recognizing the expense in order to lower perceived expenses).
- Methods of depreciation or estimates of the useful life of assets that do not correspond to the overall industry.
- A weak system of internal control.
- Too many complex related-party or third-party transactions which do not appear to add tangible value (to conceal debt from the balance sheet).
- The firm is close to breaching their debt covenants.
- The auditor was replaced, resulting in a missed accounting period.
- A disproportionate amount of managements' compensation from bonuses based on short term targets.

For Internet advertising click fraud, Wiley [8] and MECLabs [9] suggest hints of fraud such as observing unusual peaks in impressions, unusual peaks in the number of clicks, failure to see an increase in conversions when there are peaks in clicks, a drop in the number of page views per visitor during peaks in clicks, large numbers of clicks coming from the same IP address or range of IP addresses, click throughs coming from geographical areas where the firm does not do business, and a higher rate of people clicking the ad and then immediately returning to the search page during peaks in clicks. For insurance claims for bodily injury fraud, red flag indicators might be [10]: The

***Corresponding author:** Linda L Golden, Centennial Professor in Business and Professor of Marketing, The University of Texas-Austin, USA, Tel: 512-471-1126; E-mail: utlindagolden@gmail.com

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insured has history of prior claims, there is no objective evidence of injury, the claimant history of prior claims, the only injury is strain or sprain, there is no emergency treatment given at scene, non-emergency treatment is delayed, and/or there is no police report at scene.

In all of the above examples the indicators raise fraud suspicion level but do not clearly or reliability identify the fraud in and of themselves: There may be other explanations for any one of the red flags being set off. The question is how to combine these indicators or hints of fraud into an overall assessment of fraud suspicion. As Bolton and Hand and Bolton (2002) [11] comment when discussing approaches to fraud detection "One can think of the objective of the statistical analysis as being to return a *suspicion score…*".

As shown, for many applications in accounting and marketing there may be no identifiable "dependent variable" or fraud label upon which to train a standard statistical model, such as logistic regression, in order to detect fraud. The company must attempt to detect such fraud never-the-less, even when there is no measureable dependent variable. This article points to a new statistical method, PRIDIT (Principal Component Analysis of RIDITs), for identifying fraud in this "no dependent variable" setting.

PRIDIT can better utilize statistically the "hints" about fraud that is itself not easily observed than can factor or cluster analysis on the same data [12]. This leads to more accurate fraud prediction for more difficult fraud identification situations. In short, PRIDIT can predict without a training sample, which has applications beyond the fraud application discussed here.

In conclusion, there are relatively few methodologies available for creating an overall suspiciousness score for each entity under investigation when there is an ensemble of red flag binary predictor variables or hints of fraud, but no definitive dependent variable that designates whether or not fraud occurred. Cluster analysis and Kohonen feature maps are possibilities; however, they suffer from defects in identifying fraud clusters and in being able to numerically rank entities in a suspiciousness scale for further investigation. PRIDIT analysis assumes there are a collection of predictor variables (red flags or fraud indicators variables) that can be observed for each entity and that there is a "latent variable of "fraud suspiciousness" that underlies the probability that a response on a particular indicator variable will be answered in the affirmative or negative. Using this new techniques, the manager can (1) assess the relative likelihood of fraud in the entity being studied, (2) discover which predictor variables are of most importance in uncovering the fraud, (3) rank order the entities in terms of their relative suspicion level, and (4) be able to incorporate the fraud propensity score produced by PRIDIT as an input into further fraud misbehavior investigations.

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