The importance of moral hazard and the risk of fraud have been long recognized and studied in the insurance markets (Arrow, 1963). Although broadly recognised, the existence of moral hazard and insurance fraud is difficult to observe directly. When asymmetric information exists such that the insurer cannot perfectly observe the objective loss distribution, the insured or claimants may have an incentive to try to affect the probability of accidents, the amount of loss resulting from an accident, or the amount of insured loss following the accident (ex-post moral hazard). The claimants take advantage of their asymmetric information about the state of nature following the accident, inflating the number of claims filed or exaggerating the amount of the loss claimed (Cummins & Tennyson, 1996; Meyer *et al.*, 1995).

The essential components of fraud are the intent to deceive and the desire to induce an insurer to pay more than it otherwise would. Fraud is a fact of social behaviour having increasingly important consequences including loss of revenues to businesses, government, and society. Fraud is also expensive, driving up cost for detection and fraud risk reduction. As a result, active fraud control has gradually become an integrated part of business decision-making processes. Insurance companies must deal with fraud perpetrated by consumers on the firm and spend money on fraud detection and monitoring. A lot of research has focused on the fraud detection efforts and the frequency of fraud, that is, assessing and ranking the fraud suspiciousness of individual claims, currently most of which are parametric and supervised.[1] Derrig & Ostaszewski (1995) and Viaene *et al.* (2002) focus on the ex-post moral hazard and frequency of fraud. Similar, Artís *et al.* (1999) use discrete choice models to estimate the presence of fraud in claims, subject to previous knowledge of insureds' behaviours in the Spanish insurance market. Unsupervised methods for insurance fraud detection are discussed by Ai *et al.* (2009), Ai *et al.* (2013) and Brockett *et al.* (2002).

Numerous studies on automobile insurance fraud have been conducted since the 1990s. Derrig *et al.* (1994) investigate fraud and abuse in Massachusetts' automobile insurance claims. Caron & Dionne (1999) examine similar problems using Canadian data. Cummins & Tennyson (1996) find that attitudes towards fraud significantly affect automobile liability claims. Later studies develop techniques to identify or classify fraudulent claims (Tennyson & Salsas-Forn, 2002; Weisberg & Derrig, 1998). Predictive techniques are used to predict value for a certain target variable, such as credit scoring to predict repayment behaviour of loan applicants, and logistic regression models, both binary and multinomial logit models, are used for detecting manipulation such as dishonest insurance claims (Major & Riedinger, 2002; Olinsky *et al.*, 1996). Artís *et al.* (2002) find a significant portion of the claims that were previously classified as legitimate contain omission errors, and thus are likely to be fraudulent. Further, Hausman *et al.* (1998) shows that ignoring potential misclassification of a dependent variable can result in biased and inconsistent coefficient estimates when using standard parametric specifications.

These studies are followed by Caudill *et al.* (2005) who find that a multinomial logit (MNL) model can be used to identify misclassified claims. They argue that identifying fraudulent claims is similar in nature to several other problems in real life including medical and epidemiological problems. They describe the methodology that can be used to produce parameter estimates with a dataset containing misclassified dependent variables. Further, they estimate the proportion of fraudulent claims for car damage that are erroneously classified as honest by an insurance company. The procedure is based on a transformation of the standard MNL likelihood function into a missing data formulation to which the expectation maximization (EM) algorithm can be applied (Dempster *et al.*, 1977). The methodology has also been

[1] Predictive modeling can be divided into two major kinds of modeling, referred to as supervised and unsupervised learning, distinguished primarily by the presence or absence of dependent/target variable data in the data set used for modeling.

used to identify misleading response rates in a survey used to collect information on cheating behaviour (Caudill & Mixon, 2005) and to estimate the impact of misclassified observations on an analysis of hidden unemployment in six European economies (Caudill, 2006).

Further, Pinquet *et al.* (2007) present a statistical approach which counteracts selection bias without using a random auditing strategy. The model is estimated on the fraud database from the Spanish insurance market, used by Artís *et al.* (2002) and Caudill *et al.* (2005). They also use the fraud indicators from these studies, which reflect information obtained from claim reports. Also Belhadji *et al.* (2000) use these fraud indicators systematically in order to isolate the indicators which are most significant in predicting the probability that a claim may be fraudulent. Bermúdez *et al.* (2008) use an asymmetric or skewed logit link to fit this fraud database as well as the fraud indicators. Their results of estimating the standard logit model using maximum likelihood are very similar to those obtained by Artís *et al.* (2002) and Caudill *et al.* (2005).[2]

Afterwards, Caudill *et al.* (2011) develop a generalization of the MNL model they call the latent choice multinomial logit (LCMNL) model in order to investigate the possibility of hypothetical bias in the contingent valuation method (the situation in which stated willingness to pay is higher than the actual willingness to pay). This model allows for within-choice parameter heterogeneity. With cross-choice parameter constraints imposed, the LCMNL model can be interpreted as either a model for misclassification or a generalization of the pooling test of Cramer & Ridder (1991). Further, Martinez & Baerenklau (2015) implement a post-classification strategy that simultaneously detects misclassified land use observations and incorporates corrections into a LMNL land use model. This strategy is tested using both Monte Carlo simulations and a time series dataset based on supervised classification of remotely sensed data corresponding to land use decisions. Amini & Gallinari (2003) use the classification expectation maximization (CEM) algorithm, which makes use of both unlabeled data and of a probabilistic misclassification model for these data. They show experimentally that modeling the stochastic labeling noise, increases notably the performance, especially when only small labeled datasets are available. Finally, Bolin & Finch (2014) investigate the impact of initial training data misclassification on several statistical classification and data mining techniques. Results show decreased classification accuracy as sample size, group separation and group size ratio decrease. For a review of literature on the application of data mining techniques for the detection of financial fraud, see Ngai *et al.* (2011).

In our study, we address the problem of misclassified observations, which makes the observed fraudulent and observed honest too similar. This is relevant in insurance claims data, tax data and even medical or diagnostic data. We explore the problem solution proposed by Caudill *et al.* (2005) to estimate the model by the EM algorithm for missing data and to identify the claims that probably are fraudulent. Since Caudill *et al.* (2005) use real data from the Spanish car insurance fraud, we want to examine whether the EM algorithm actually provides an improvement over other fraud detection methods. We contribute to the existing literature by evaluating the performance of the EM algorithm for fraud detection, as compared to perfect information scenario and binomial logit model. Our results directly show how much estimation accuracy we lose due to not having perfect information, and the improvement in performance we achieve over the binomial logit approach.

[2] Artís *et al.* (1999), Artís *et al.* (2002), Belhadji & Dionne (1997), Belhadji *et al.* (2000), Caudill *et al.* (2005) and others estimate discrete choice models for fraud behaviour from a non-Bayesian point of view. Bayesian analysis of fraud behaviour in the automobile insurance market is implemented in Bermúdez *et al.* (2008), Viaene *et al.* (2002) and Viaene *et al.* (2007).

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