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Claims Auditing in Automobile Insurance: Fraud Detection and Deterrence Objectives

Sharon Tennyson
Pau Salsas-Forn

Abstract

Research on insurer management of opportunism in claiming has developed in two parallel literatures. One is a theoretical literature on insurance contracting that yields predictions about the nature of optimal auditing strategies for the deterrence of fraud. The other is a literature based upon statistical analysis of claims that yields empirical strategies for the detection of fraudulent claims. This article links the two literatures by providing an empirical assessment of insurers' auditing practices in relation to theoretical predictions. The analysis makes use of a data set on the disposition of more than 1,000 randomly selected automobile personal injury protection claims settled in the state of Massachusetts. The findings of the article are consistent with the use of rational auditing strategies by insurers and with the use of audits for both deterrence and detection.

Introduction

The issue of claims fraud (illegitimate claims) and buildup (exaggerated loss amounts) is a major concern among automobile insurance companies. Empirical studies have concluded that large percentages of claims appear to involve fraud or exaggeration.[1] For example, studies of automobile personal injury claims in the state of Massachusetts have found that anywhere from one-quarter to three-quarters of claims show some evidence of fraud or buildup (Weisberg and Derrig, 1991, 1996). The Insurance Research Council (1996) analyzed claims from nine states and found that 21 to 36 percent of the claims involved suspected fraud or buildup.[2] In all of these studies,

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[1] More econometrically oriented studies by Cummins and Tennyson (1996) and Abrahamse and Carroll (1999) also find evidence of fraud or buildup in automobile insurance markets.

[2] In both sets of studies, the determination of suspicion was made by insurance company claims reviewers. Irrespective of whether these reviewers are correct in their assessments, the results provide evidence that the problem is perceived to be large by insurance companies.

the vast majority of suspicious claims involved potential buildup rather than outright fraud. Consistent with this concern, the focus of this article is on buildup.

In the presence of buildup, the active verification of claims through investigation or auditing is an important claims management tool. The role of auditing is recognized in both insurance theory and practice. A large theoretical literature examines the design of auditing strategies in the insurance claiming context.[3] This literature derives theoretically optimal auditing strategies that minimize the total costs incurred from buildup, where the costs include both the costs of performing audits and the costs of paying built-up claims that are not detected. The key insight from theory is that the primary role of auditing in an optimally designed system is the deterrence of buildup rather than its detection.

Statistical literature aimed at designing better fraud detection systems is also growing.[4] This literature focuses on the practical complexities faced by an insurer determining which claims to audit when claims differ in many characteristics. This literature provides insights into auditing for the detection of built-up claims. Auditing as a deterrent mechanism has received less attention in this literature, and audit system success is typically measured by the reduction in payment amounts on audited claims or by the number of fraudulent or built-up claims detected.

While clearly different in focus, these two approaches need not be incompatible. The theoretical literature on auditing of necessity makes a number of simplifying assumptions about the nature of claims and the information available to the insurance company, and thus yields only very general predictions about optimal auditing strategies. For example, the theory predicts that larger claims, and claims for which the potential for opportunism is greater, should be audited with a higher probability than other claims (Picard, 2000). Consistent with this, the empirically based design of fraud detection systems can be viewed as an attempt to identify those specific categories of claims that should be audited with higher probability, given complex claims characteristics and imperfect knowledge of the degree of opportunism in the claiming population.

Nonetheless, the difference in focus across the two literatures raises questions about the use and role of auditing in insurance markets. While several studies examine the determinants of claims audits in practice (for example, Weisberg and Derrig, 1996, 1998), to our knowledge no studies have examined auditing practices in relation to the predictions of theory. Nor has the relative importance of the detection versus deterrence objectives in auditing been examined. This article analyzes claims auditing in an automobile insurance market to provide empirical evidence on these issues. The article makes use of a data set of individual automobile insurance claims that includes information regarding the handling of the claim by the insurance company.

[3] See, for example, Kaplow (1994); Picard (1996); Bond and Crocker (1997); and Boyer (1998), among others. Picard (2000) provides an excellent in-depth review of this theoretical literature.

[4] Studies in automobile insurance include Artís, Ayuso, and Guillén (2001); Belhadji, Dionne, and Tarkhani (2000); Brockett, Xia, and Derrig (1998); Derrig and Ostaszewski (1995); and Derrig, Weisberg, and Chen (1994). There are also studies in other markets such as health care (for example, Rosenberg, Andrews, and Lenk [1999]; Sokol et al. [2001]) and workers' compensation (see Derrig and Kraus [1994]).

The outline of the remainder of the article is as follows. "Massachusetts PIP Claims" describes the database of automobile insurance claims. "Claims Auditing Patterns" describes the patterns of auditing observed in the data. "The Economic Role of Auditing" develops specific hypotheses to be tested. "Econometric Analysis of Auditing" presents an econometric analysis of auditing and interprets the results, followed by the conclusion.

Massachusetts PIP Claims

This article uses data on automobile personal injury protection (PIP) claims settled in the state of Massachusetts. PIP coverage is first-party injury protection provided under no-fault automobile insurance systems. This coverage indemnifies the insured, the family, or other occupants of the insured's car for losses from accident-related injuries, regardless of fault in the accident. In Massachusetts, PIP covers 100 percent of medical expenses and 75 percent of wage losses, up to a maximum of $8,000. However, if the claimant has private health insurance, medical and related losses in excess of $2,000 are first submitted to the health insurance provider. Any amounts, including deductibles, that are not covered by the health insurer are paid under the PIP coverage (up to the $8,000 limit).

The PIP claims data were obtained from a Massachusetts Automobile Insurers' Bureau (AIB) study of claims handling. The initial sample consisted of 1,207 randomly selected PIP claims settled by the ten largest insurers in the state in 1993. The claims data were reviewed and coded into the claim survey form by non-company coders trained by the AIB. The survey form reported information regarding the accident, the claimant and the claimant's injuries, the claimed amount, and the amount paid by the PIP insurer. In addition, the survey reported whether the claim was settled routinely or whether non-routine investigation was undertaken. For investigated claims, the survey also reported the type(s) of investigation undertaken and the results of each investigation—whether the investigation confirmed, refuted, or created doubt about the audited elements of the claim.

In constructing the claims sample for analysis, we eliminated claims for which the settlement process was incomplete, claims that were closed without payment due to statutory ineligibility for coverage, claims for which the expenses reported in the data were known to be less than the full amount of the claimant's loss, and claims for which no loss amount was reported.[5] These selection criteria produced a sample of 1,091 claims for use in the analysis.

Table 1 displays the distribution of claimed amounts in the sample of 1,091 claims. Claims ranged greatly in size, from a minimum of $10 to a maximum of $104,487.[6]

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[5] Statutory ineligibility occurs if the claimant had no PIP coverage, the claimant was under the influence of alcohol or drugs in the accident, or the claim was covered under workers' compensation. Under-reporting of expenses occurred in some claim files when only the maximum amount that could be paid under PIP coverage was reported, rather than the full amount of the claimant's loss. We eliminated these claims due to concerns that the insurer's auditing strategy might have been affected by information not included in our data set.

[6] Although the PIP limits are $8,000, a few claims were recorded for amounts greatly exceeding this limit. This may be because the PIP claim was linked to a bodily injury claim, for which the policy limits are much greater. The data were checked extensively, and no evidence emerged

TABLE 1
Distribution of PIP Claim Amounts

Mean	2, 761.44
Standard Deviation	4, 755.46
Minimum	10.00
25th Percentile	488.00
Median	1, 765.00
75th Percentile	3, 464.00
Maximum	104, 487.00

As in most insurance claims distributions, however, many more claims were for small amounts than for large amounts. The mean claim amount was $2,761.44, and the median claim amount was $1,765.00.

Despite the relatively low coverage limits under PIP, automobile insurers have found it necessary to monitor PIP claims for buildup. This may be due in part to the relationship between PIP claims and tort eligibility. In Massachusetts, an automobile-related injury may be eligible for a bodily injury liability (BIL) claim if the claimant's medical expenses exceed $2,000.[7] Liability claims are compensated on an at-fault basis but are not subjected to the strict coverage limitations of PIP. BIL insurance claimants may be compensated for the full value of documented losses and for undocumentable losses such as "pain and suffering" (through general damages awards). Because a claimant may file a BIL claim only if medical expenses filed under the PIP claim exceed the tort threshold, significant incentives exist for PIP claims buildup.

An interesting feature of the PIP claim distribution is thus the relationship between claim amounts and claimant tort eligibility. Under Massachusetts liability rules, all injured passengers and pedestrians, and injured drivers who are less than 50 percent at fault in the accident, are eligible for BIL compensation if medical losses exceed $2,000. Table 2 shows the cross-tabulation of claimant fault and reported loss amounts by whether the reported loss is below or above the tort threshold. The table shows strong suggestive evidence of claimant opportunism.[8]

Notice in the table that the claims are approximately equally divided into the below-$2,000 and above-$2,000 partitions (556 claims and 535 claims, respectively). However, the distribution of fault among claimants is very different for claimed amounts below and above $2,000: 148 of the claimants with reported losses below the tort threshold

of misrecording of claim amounts for these large claims. To make sure that our results were not unduly influenced by the large claims, we replicated our analysis omitting these claims and found no impact on the conclusions.

[7] PIP claims fraud may be profitable in and of itself in states that have higher compensation limits. For example, in New York (with a payment limit of $50,000), PIP claim frequency and severity are sharply higher than the national average, despite a verbal threshold for tort claims. The high costs are thought to be due in part to organized fraud and claims buildup (Mitchell, 2001).

[8] Similar findings were reported by Derrig, Weisberg, and Chen (1994).

TABLE 2
Distribution of PIP Claim Amount by Claimant Fault

	Claim < $2,000	Claim ≥ $2,000	Total
Claimant Not At Fault	408	486	894
Claimant At Fault	148	49	197
Total	556	535	1091

were at fault in the accident (i.e., 26.6 percent), but only 49 of the claimants with reported losses above the tort threshold were at fault in the accident (8.2 percent). This pattern suggests that either injured parties who were not at fault in their accident may have exaggerated their losses to gain BIL eligibility (evidence of claims buildup) or not-at-fault parties with medical expenses meeting the tort threshold were more likely to file a PIP claim due to their BIL eligibility (evidence of claims-reporting moral hazard).[9]

CLAIMS AUDITING PATTERNS

An insurance company can audit using a variety of methods. The non-routine handling methods included in the AIB survey form are an independent medical exam (IME); a medical audit; a site investigation; recorded or sworn statements from the claimant, the insured, and/or a witness to the accident; referral to a Special Investigative Unit (SIU); and an activity check. An IME involves an examination of the claimant by a doctor chosen by the insurance company. A medical audit involves a review of medical utilization and charges by a nurse or other medical professional hired by the insurance company. A site investigation involves a claims adjuster visiting the scene of the accident to determine the facts of the accident. Referral to an SIU involves active investigation by a specially trained anti-fraud unit of the insurance company. An activity check involves surveillance of the claimant or interviews with neighbors and others familiar with the claimant's activities.

Table 3 summarizes the relative use of the different audit techniques and the outcomes of audits. In total, the data contained 553 instances of audit. The most prevalent auditing technique was the recording of statements taken from a party to the accident (the claimant, the insured, or a witness), used 269 times. The second most frequent technique was an IME, used in 180 cases.[10] Sworn statements, activity checks, medical audits, site investigations, and SIU referrals were used much less frequently.

In addition to reporting the audit methods used for each claim, for each audit the claims survey recorded whether it resulted in the audited information being "confirmed," "refuted," or "doubted." Table 3 also reports the relative frequency of these outcomes for each of the auditing methods reported in the survey. The most frequent result of an audit was confirmation of the information, occurring in nearly 75 percent

[9] Chi-square test statistic = 56.17 (p value = 0.00).

[10] The high rate of use of IMEs may arise because the Massachusetts PIP insurance policy requires a claimant to cooperate if an IME is requested.

TABLE 3
Audit Methods and Outcomes

	Frequency	Information Confirmed (%)	Information Doubted (%)	Information Refuted (%)
Independent Medical Exam	180	108 (60.0)	59 (32.8)	13 (7.2)
Medical Audit	29	12 (41.4)	13 (44.8)	4 (13.8)
SIU Referral	21	10 (47.6)	6 (28.6)	5 (23.8)
Activity Check	7	3 (42.9)	3 (42.9)	1 (14.3)
Site Investigation	35	26 (74.3)	7 (20.0)	2 (5.7)
Recorded Statement	269	246 (91.4)	15 (5.6)	8 (3.0)
Sworn Statement	11	7 (63.6)	3 (27.3)	1 (9.1)
Total Audits	552	412 (74.6)	106 (19.2)	34 (6.2)

Note: The data contained 553 audits, but outcome information was missing for one audit.

of all audits. Only 6.2 percent of audits refuted the audited information. The highest percentages of refuted information resulted from SIU referrals (23.8 percent), activity checks (14.3 percent), and medical audits (13.8 percent). Site investigations refuted claimed information only 5.7 percent of the time, and recorded statements yielded this result in only 3 percent of cases.

The high prevalence of recorded statements in the data raises some questions about whether recorded statements are appropriately included in the definition of audits. Some insurers may routinely record statements as a form of record keeping. In this case the recording does not necessarily represent an active investigation technique. However, the routine use of recorded statements may represent an audit method employed with fraud deterrence in mind. Because of the potential ambiguity regarding their purpose, the remainder of this article examines auditing, both including recorded statements as a form of audit (denoted by "all audits") and excluding recorded statements from audits (with the remaining methods termed "investigative audits").

While 553 audits are observed in the data, only 358 claims (32.8 percent of the sample) were subjected to audit. As can be seen in Table 4, this difference arose because some claims were audited more than once. Of the 358 audited claims, 229 (64.0 percent) were audited using only one technique. Of these 229 claims, 115 were audited using only one or more recorded statements. This left 243 claims audited using the other investigative techniques. Of these 243 claims, the majority (212, or 87.2 percent) were investigated only once.[11]

Table 5 reports the auditing outcome for each claim in the sample that was subjected to audit. The table reports results for both all audits and investigative audits. The audited claims are grouped into two categories: those that were audited only once and those

[11] In the analysis of auditing by claim, we counted the use of multiple recorded or sworn statements as a single auditing technique, so the number of claims for which (perhaps multiple) recorded statements were used does not add up to the number of recorded statements in the data.

Table 4
Audit Intensity

Number of Methods	Audited Claims (%)	Investigated Claims (%)
1	229 (63.97)	212 (87.24)
2	85 (23.74)	23 (9.47)
3	28 (7.82)	6 (2.47)
4	11 (3.07)	2 (0.82)
5	4 (1.12)	0 (0.00)
6	1 (0.28)	0 (0.00)
Total	358 (100)	243 (100)

Table 5
Audited Claims and Audit Outcomes

	Number of Claims	All Elements Confirmed (%)	Some Elements Doubted (%)	Some Elements Refuted (%)
ALL AUDITS				
One Method	229	154 (67.2)	63 (27.5)	12 (5.2)
More Than One Method	128	91 (71.1)	23 (18.0)	14 (10.9)
Total	357	245 (68.6)	86 (24.1)	26 (7.3)
INVESTIGATIVE AUDITS				
One Method	211	131 (62.1)	65 (30.8)	15 (7.1)
More Than One Method	31	11 (35.5)	13 (41.9)	7 (22.6)
Total	242	142 (58.7)	78 (32.2)	22 (9.1)

Note: Audit outcome information was missing for one claim.

that were audited more than once. The table reports the fraction of audited claims for which audits resulted in all elements of the claim being confirmed, the fraction for which at least one audit resulted in the audited information being doubted, and the fraction for which at least one audit resulted in the audited information being refuted. If any audit resulted in any element of the claim being refuted, we report that claim in the "Some Elements Refuted" column; that is, each audited claim is categorized by the worst outcome from all of the audits performed.

Of the 357 audited claims for which we have outcome data, 245 (68.6 percent) were confirmed by all audit techniques employed. Only 7.3 percent of audited claims had information refuted by audit, while in the remaining 24.1 percent of claims the audit produced some doubt about the audited information. Moreover, claims audited using more than one technique were not more likely to be doubted or refuted than claims audited only once. In addition, 67.2 percent of claims audited once and 71.1 percent of claims audited more than once were confirmed by all audits, while 32.7 percent audited once and 28.9 percent audited more than once were not confirmed. These differences are not statistically significant.[12]

The outcomes for investigative audits showed a somewhat different pattern. Similar to all audits, the most frequent investigative outcome overall was confirmation of the claim, which occurred in 142 cases (58.7 percent). Investigations refuted information in only 22 claims (9.1 percent) and created doubts for 78 claims (32.2 percent). However, claims investigated with more than one method were less likely to be confirmed than claims investigated only once. While 62.1 percent of claims investigated only once were confirmed, only 35.5 percent of claims investigated more than once were confirmed by all audits. And while 37.1 percent of claims investigated only once were not confirmed, 64.5 percent of claims investigated more than once were not confirmed. These differences are statistically significant.[13]

Due to insurers' use of many different investigative techniques, the interpretation of this latter finding is unclear. It could be indicative of a sequential decision-making process for investigative audits, in which additional investigation (for detection) is undertaken if a first investigation results in information being doubted or refuted.[14] However, it may also reflect that fact that different investigative methods are being used to determine different types of information.

THE ECONOMIC ROLE OF AUDITING

The audit patterns in the data revealed that less than one-third of claims were audited, and if one considers only investigative audits, only about one-fifth of claims were audited. As seen, the majority of claims were audited using only one method, and the most common outcome of an audit was to confirm the claim. Audits only rarely refuted any elements of a claim.

The high percentage of audited claims confirmed is a particularly notable finding. If the detection of fraud or buildup is the sole objective of auditing, this finding suggests that insurer audit systems may not be fully efficient. However, recognizing that audits may serve both detection and deterrence functions, this finding need not indicate a poorly performing system. In fact, a low rate of detection could be evidence of audit system success, if it occurs because the rate of falsified claiming is low due to the deterrent effect. To determine which interpretation is more correct requires a closer examination of the predicted audit patterns under a deterrent versus a detection objective in auditing.

Economic theories of optimal auditing strategies utilize a principal–agent framework, under which it is posited that the insurer (the principal) designs auditing rules before receiving any claims. The rules are designed recognizing that a claimant (the agent) has the ability to misrepresent the amount of a loss and will report the amount of loss

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[12] The chi-square test statistic for the difference in confirmation rates is 0.56, which has a p value of 0.453.

[13] The chi-square test statistic is 7.89, which has a p value of 0.005.

[14] We have no data on the sequencing or timing of investigations and thus cannot explore this hypothesis further.

that maximizes the expected payoff (or expected utility of payoff).[15] The insurer may audit a claim to determine the true loss amount, but auditing is costly. The insurer's aim is to choose auditing rules that minimize (subject to constraints) the total costs of claims buildup, including the cost of both undetected built-up claims and auditing claims.

Although derived within a complex informational structure, the theoretically optimal auditing strategy conforms to basic economic principles. To minimize total costs, the insurer should audit to the extent that the expected marginal costs of auditing are just equal to the expected marginal savings from auditing. An important realization is that the savings from audits are not just the savings in claims costs from detecting built-up claims. Additional savings will be due to the deterrence of buildup that occurs when claimants know that claims are being audited. Under ideal conditions, the optimal auditing strategy will completely eliminate buildup, and thus all savings will stem from deterrence. Under more realistic conditions, the optimal auditing strategy will serve partly as a deterrent and partly to identify those claims that are fraudulent or built up (Khalil, 1997).[16]

This optimal auditing strategy, derived from the economic approach, has several intuitively appealing properties. First, auditing will be random rather than deterministic; that is, each claim will be audited with some probability less than one. In combination with the use of penalties imposed upon those who are discovered to have built up a claim, random auditing allows the insurer to conserve on audit costs relative to deterministic auditing. Although some claims are not audited, buildup is nonetheless deterred by the anticipation of penalties imposed if a claim is audited and found to be built up.[17]

In addition, only claims for losses above some threshold amount will be audited, because the potential benefits of audits must be weighed against the audit costs. Holding audit costs fixed, the potential benefits of audits will be greater for higher valued claims than for smaller claims. In practice, given the different costs of the different audit methods, this prediction implies that the probability that a claim is audited will be positively related to the size of the claim.

Finally, the probability of audit will be positively related to the fraction of claimants in the population who are willing to build up a claim (Picard, 1996). While it is hard to measure the fraction of claimants willing to do this, the prediction can be interpreted

[15] A large theoretical literature examines the problem of efficient contract design under information asymmetry, in which the problem of insurance claims buildup is just one example. The theoretical problem of designing an optimal contract with costly verification was first examined by Townsend (1979).

[16] Within the theoretical economics literature, the distinction between a pure deterrence objective and some detection objectives can be framed in terms of whether insurers can or cannot pre-commit to an audit strategy. If insurers can pre-commit to a known auditing strategy before any claims are filed, then the optimal auditing strategy will completely eliminate all buildup, and thus the savings from auditing arises from deterrence alone. If insurers cannot pre-commit, the optimal auditing strategy serves partially as a deterrent and partially to identify those claims that are fraudulent or built up (Khalil, 1997).

[17] Penalties may involve, for example, less generous claims settlement, change in terms of future insurance contracts, reputational penalties, or even legal prosecution.

in relation to different categories of claims. If specific claims categories are more likely to be built up than others, then the insurer must audit a higher percentage of those claims to deter buildup.

It is important to note that these characteristics of the optimal auditing strategy will also be observed in a well-designed system aimed solely at fraud detection. Fraud detection systems attempt to select the claims that are most likely to be fraudulent or built up for audit. Only those claims thought to be sufficiently suspicious will be audited, and thus auditing will appear to be probabilistic. Similarly, higher-valued claims will be more likely to be audited due to the potentially greater savings associated with detected buildup, as well as the greater likelihood of buildup among larger claims. Finally, the prevalence of auditing may vary across claims categories according to insurers' suspicions regarding the extent of fraud or buildup among different types of claims.

However, two distinctions can be made between auditing with a deterrence objective versus auditing for detection. The first regards the decision to audit. Under a deterrence objective, the likelihood that a claim is selected for audit will vary with claim characteristics defined before a review of the specific claim. Under a detection objective, an individual claim will be selected for audit based upon any characteristic thought to indicate fraud or buildup. Under either objective, the decision to audit may depend upon specific characteristics of the claim, and these may be characteristics that have been identified by some empirical model. However, only under a detection objective may more subjectively determined suspicions regarding a specific claim be used to determine an audit. Thus, the use of subjective determinations by a claims adjuster to decide upon an audit provides evidence of auditing for fraud detection.

The second distinction regards audit outcomes. If auditing is used solely to deter buildup, then although claims categories with a high potential for opportunism will be audited *more* frequently, these claims should be found to be built up *no more* frequently than other claims. This is because optimal deterrence implies that the audit probability will be adjusted across claims categories to reflect the relative likelihood of buildup. Because auditing deters the filing of built-up claims, the observed outcomes of audits across different claims categories should be random. Conversely, if auditing serves as a detection device, high-opportunism claims should be audited with greater frequency, and buildup should also be detected with greater frequency in these claims.

These predictions from theory form the basis for testing whether insurers' auditing practices are consistent with the economic decision models of auditing. The key predictions are that the probability of audit should increase with the size of the claim and that the probability of audit should increase with the degree of opportunism in the claiming environment. Different predictions under detection versus deterrent objectives also allow examination of the extent to which audit practices are consistent with a deterrent objective.

Econometric Analysis of Auditing

We develop and estimate an econometric model of claims audits. Because only a relatively small percentage of claims in our data were audited or investigated with more than one method, we group claims into two categories: those that were not audited and those that were audited (once or more than once). We estimate separate models for the probability of any audit and the probability of investigative audit. Recall that the distinction between the two audit-variable definitions is that recorded statements are not included in the investigative audits.

The Empirical Model

Both the economic theory of optimal auditing and the design of fraud detection systems predict that each claim will be audited with some probability less than one and that the probability a claim is audited will depend upon the expected gains from auditing. Economic theory recognizes that the expected gains from audits include the cost savings from both detected buildup and deterring claims buildup. The expected gains from auditing—whether for detection or for deterrence—are related to characteristics of the claim.

Therefore, characterize the expected gains (G_i) (net of audit costs) from the auditing claim (i) as a function of characteristics of the claim (X_i):

$$G_i = g(X_i) + \varepsilon_i, \tag{1}$$

where ε_i is a random error term. A claim will be audited if G_i is greater than 0.

G_i is not directly observed in these data, but given a probability distribution function $F(\varepsilon_i)$, the probability that a claim will be audited can be expressed as a function of the claim characteristics as follows:

$$\Pr(G_i > 0) = \Pr[\varepsilon_i > -g(X_i)] = 1 - F[g(X_i)]. \tag{2}$$

The empirical model estimates the probability that $G_i > 0$; that is, the probability that a claim is audited given X_i. Use of the logistic model assumes that the error term follows a logistic distribution with zero mean and constant variance across claims. As seen, economic theory predicts that the claims characteristics determining the probability of audit include the claimed amount of loss and characteristics related to the degree of opportunism in claiming. The theoretical relationship between the audit probability and the claim amount is increasing but not necessarily linear. We will account for this potential nonlinearity by allowing the audit probability to depend upon both the claimed amount of loss and the claimed amount squared.[18]

The distinction between auditing only for deterrence and auditing (wholly or in part) for detection can be seen in the claims characteristics upon which insurers condition their audits. When auditing for detection, the auditing decision will depend upon any characteristics of the claim that the adjuster finds suspicious. This implies that the probability of audit may depend upon both predetermined objective characteristics of the claim and subjective determinations of the adjuster. In contrast, when auditing solely for deterrence, insurers precommit to an auditing strategy; hence the auditing probability will vary only with predetermined characteristics of the claim. These

[18] Economic theory predicts that claims below a certain threshold amount will not be audited. However, the threshold depends on the cost of auditing. Given the variety of available auditing techniques and the differing costs of using those techniques, we do not attempt to identify the no-audit region(s).

predetermined characteristics should include claim size and indicators of the potential for opportunism.

To distinguish between predetermined and subjective characteristics of a claim, denote

$\mathbf{D}_i$ = a column vector of predetermined characteristics for claim i, and

$\mathbf{S}_i$ = a column vector of subjective characteristics for claim i

Assuming linear relationships, write the empirical model as

$$\Pr(G_i > 0) = \alpha_0 + \alpha_1 y_i + \alpha_2 y_i^2 + \boldsymbol{\beta}_1' \mathbf{D}_i + \boldsymbol{\beta}_2' \mathbf{S}_i + \varepsilon_i, \tag{3}$$

where α_0, α_1, and α_2 are the parameters of interest associated with the constant term, the claimed amount of loss (y_i), and the claimed amount squared (y_i^2), respectively; and $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ are column vectors of parameters for the predetermined characteristics and subjective characteristics, respectively.

Testing for evidence of an economic approach to auditing is implemented as a test of whether the probability of audit increases not only with claim size but also with predetermined claim characteristics representing greater potential for opportunism. That is, the predetermined characteristics D will be jointly statistically significant if insurers use economic decision models to determine audit strategies, regardless of whether they pursue a pure deterrence or a detection objective in auditing.

By contrast, testing for evidence of auditing (at least in part) for fraud detection is implemented as a test of the joint statistical significance of variables representing subjective suspicion characteristics of a claim. Under a pure deterrence objective for auditing, the subjective characteristics S will not be jointly statistically significant; however, under a detection objective for auditing, S will be statistically significant. We tested for the joint statistical significance of the parameters associated with both D and S using a Wald test of linear restrictions.[19]

Definition of Variables

A key explanatory variable in the model is the claimed amount of loss. This variable is measured as the sum of all medical bills and medical-related expenses (ambulance services, prescriptions, replacement services, rehabilitation services, medical equipment, funeral expenses, and others), and 75 percent of wage losses. The empirical specification includes both the claimed amount and the claimed amount squared, to allow for a potentially nonlinear relationship between the audit probability and the size of the claim.

The model includes a number of variables to test the prediction that the probability of audit increases as the potential for opportunism in claiming increases. The potential for opportunism is represented by certain characteristics of the claim. For example, the incentives to build up a PIP claim to exceed the tort-eligibility threshold make tort eligibility an indicator of opportunism. Accordingly, we include as an explanatory variable in the model an indicator of whether the claimant is eligible to file a tort claim. This variable is equal to one if the claimant was a passenger or a pedestrian, or

[19] The estimation and tests are undertaken using the SAS statistical programming package. The Wald test of linear restrictions is described in Greene (2000).

a driver who was less than 50 percent at fault in the accident, and the total medical losses exceeded $2,000.

Previous studies of insurance claiming have also found that sprain claims appear to be subject to greater degrees of opportunism (Crocker and Tennyson, 2002; Dionne and St.-Michel, 1991), due to the difficulty that medical doctors have in determining the severity of such injuries with precision (Dionne and St.-Michel, 1991). Thus, the model herein includes dummy variables for the characteristic of the claimant's most severe injury, to test the hypothesis that claims involving primarily sprain injuries are more likely to be audited than claims involving other types of injuries. Due to the small number of claims in many injury categories, the model includes dummy variables for only the injury categories of laceration, neck sprain, back sprain, and other sprain. All other primary injury types are grouped together as the excluded category. We expect to observe a significant and positive coefficient on both the tort-eligibility and the sprain injury indicators.

Previous researchers have also identified specific characteristics of claims that lead insurance claims adjusters to be suspicious of opportunism (Weisberg and Derrig, 1991). A study of PIP claims handling in Massachusetts identified ten specific claims characteristics, from among many, that were significantly related to claims experts' perceptions of the suspiciousness of a claim (Weisberg and Derrig, 1998). Our data set reports these ten claims characteristics, and the empirical model includes indicator variables for each. Table 6 defines the claims characteristics (along with summary statistics for these and the other variables used in the logistic models).

As seen from the table, for some of the claims suspicion indicators it is easy to imagine an insurer establishing an ex ante rule that a claim exhibiting these characteristics will more likely be audited. This is easily true for indicators such as "no police report," "claimant in an old, low-value vehicle," "no objective evidence of injury," and "injuries inconsistent with police report." Others that also seem possible to establish ex ante rules for include "many visits to a chiropractor," "long disability for a minor injury," and "insured felt set-up, denied fault."[20] By contrast, some of the suspicion indicators are inherently subjective in that they would have to be decided by a claims adjuster based upon his or her experiences with a specific claim. "Claimant appeared claims-wise," "insured uncooperative," and "no plausible explanation for accident" are examples of this type of indicator.[21]

Although not derived from theory, the estimated model must also include variables to control for two institutional features of the Massachusetts PIP claims payment environment. The first is an indicator variable set equal to one if the claimant has private health insurance and the value of the claim is greater than $2,000. This variable is included because health insurance becomes the primary insurance policy in Massachusetts after PIP payments of $2,000. The second institutional control is an indicator variable set

[20] For example, a threshold number of chiropractor visits or a maximum disability duration could be established via rules. Similarly, any denial of fault by the insured could be part of an ex ante audit rule.

[21] This last variable, "no plausible explanation for accident," appears to us to fall somewhere in between, possibly requiring judgment from the adjuster. Thus, we perform the Wald tests two ways, first including this among the subjective indicators and then including it among the predetermined indicators.

TABLE 6
Summary Statistics

	Frequency	Percent
Basic Claim Characteristics:		
Private Health Insurance	202	18.52
PIP Coverage Limit	65	5.96
Tort-Eligible	487	44.64
Laceration	178	16.32
Neck Sprain/Strain	161	14.76
Back Sprain/Strain	566	51.88
Other Sprain/Strain	48	4.4
Suspicion Indicators:		
No Report by Police at Scene	522	47.85
No Plausible Explanation of Accident	10	0.92
Claimant in an Old, Low-Value Vehicle	419	38.41
Insured Felt Set Up, Denied Fault	40	3.67
Claimant Appeared "Claims-Wise"	214	19.62
Insured Uncooperative	29	2.66
No Objective Evidence of Injury	675	61.87
Injuries Inconsistent With Police Report	118	10.82
Large Number of Visits to a Chiropractor	266	24.38
Long Disability for a Minor Injury	61	5.59

equal to one if the claim amount exceeds the maximum Massachusetts PIP coverage level of $8,000. Because in both of these situations the insurer's expected PIP payment is lower (all else remaining equal), the insurer should be less likely to audit the claim. Thus we expect to observe a negative relationship between these variables and the probability that a claim is audited.

Estimation Results

Table 7 reports the results of the logistic model estimation. There are only relatively small differences in the estimation results under the alternative definitions of what constitutes an audit, and the estimation results overall are consistent with the theoretical predictions. However, as would be expected if recorded statements were sometimes used for non-investigative purposes, the model fit is superior when the probability of an investigative audit is the dependent variable.

In all model specifications, the probability of audit is positively and significantly related to the claim amount and negatively and significantly related to the claim amount squared. Thus, the audit probability increases with claim size but at a decreasing rate. The indicator variables for sprain-related claims are positive and significantly

Table 7
Logistic Models of Audit Probability

	All Audits		Investigative Audits	
	Model 1	Model 2	Model 1	Model 2
Intercept	−2.4270* (0.2678)	−2.3243* (0.2975)	−4.16* (0.3817)	−4.1691* (0.4286)
Claimed Amount	3.09E-04* (7.30E-05)	2.77E-04* (7.70E-05)	4.64E-04* (8.70E-05)	4.64E-04* (9.20E-05)
Claimed Amount Squared	−1.14E-08* (3.78E-09)	−1.00E-08* (3.75E-09)	−1.77E-08* (4.95E-09)	−1.69E-08* (4.81E-09)
Private Health Insurance	−0.2557 (0.1826)	−0.2170 (0.1887)	−0.0865 (0.1934)	−0.0176 (0.2023)
PIP Coverage Limit	−0.4538 (0.4505)	−0.2934 (0.4602)	−0.4771 (0.4877)	−0.4133 (0.5001)
Tort-Eligible	0.7527* (0.2113)	0.5226* (0.2229)	0.8164* (0.2484)	0.4159 (0.2641)
Laceration	0.8050* (0.3084)	0.7376* (0.3157)	0.6671 (0.4776)	0.6696 (0.4914)
Neck Sprain/Strain	0.7471* (0.2983)	0.5107 (0.3265)	1.3918* (0.3966)	0.8915* (0.4426)
Back Sprain/Strain	0.8477* (0.2466)	0.5980* (0.2732)	1.655* (0.3365)	1.2500* (0.3751)
Other Sprain/Strain	1.1196* (0.4014)	0.9554* (0.4175)	1.9424* (0.504)	1.7734* (0.5301)
No Report by Police at Scene	–	−0.2854 (0.1561)	–	−0.1093 (0.1879)
No Plausible Explanation of Accident	–	1.0101 (0.7203)	–	0.0299 (0.8502)
Claimant in Old, Low-Value Vehicle	–	−0.1098 (0.1496)	–	0.0205 (0.1757)
Insured Felt Set Up, Denied Fault	–	0.8664* (0.3575)	–	0.0667 (0.4447)
Claimant Appeared "Claims-Wise"	–	0.3111 (0.1945)	–	0.6060* (0.2038)
Insured Uncooperative	–	0.6617 (0.4287)	–	1.0268* (0.4733)
No Objective Evidence of Injury	–	0.0926 (0.1667)	–	0.1347 (0.2039)
Injuries Inconsistent With Police Report	–	0.3496 (0.2377)	–	0.2371 (0.2795)
Many Visits to Chiropractor	–	0.7541* (0.1812)	–	0.8660* (0.1937)
Long Disability for Minor Injury	–	−0.2787 (0.3055)	–	−0.5780 (0.3198)
Likelihood Ratio Statistic	141.04	181.50	227.67	277.66
Percent Concordant	71.4%	74.9%	79.8%	82.6%

Standard errors are in parentheses.
* Indicates parameter is significantly different from zero at better than the 5 percent significance level, 2-sided test. The Wald chi-square test statistic for the joint significance of all suspicion indicators is 45.098 ($p < 0.0001$) in column 2 and 47.419 ($p < 0.0001$), in column 4. The Wald chi-square test statistic for the joint significance of the predetermined indicators is 31.465 ($p < 0.0001$) in column 2 and 25.275 ($p = 0.0007$) in column 4. The Wald chi-square test statistic for the joint significance of the subjective indicators is 8.451 ($p = 0.0376$) in column 2 and 15.918 ($p = 0.0012$) in column 4.

related to the probability of audit, with sprains other than back or neck sprains appearing to receive the greatest likelihood of scrutiny. The tort-eligibility indicator variable is also positive and statistically significant in three of the four model specifications, demonstrating that insurers are more likely to audit claims that exceed the tort threshold.

In both sets of models, almost all of the suspicion indicators are positively related to the probability of audit, as expected. Taken as a whole, the suspicion indicators are also jointly statistically significant in both models. Only a few of the individual suspicion indicators are statistically significant. Using all audits as the dependent variable, two indicators are significantly related to the probability of audit: "insured felt set up, denied fault" and "many visits to chiropractor" are both positive and significantly related to the probability of audit. These variables are among the predetermined suspicion indicators in the model. With investigative audits as the dependent variable, "many visits to chiropractor" remains statistically significant, and two of the subjective suspicion indicators are also significant and positively related to the probability of audit: "claimant appeared claims-wise" and "insured uncooperative."

The results from analyzing the joint significance of the predetermined and subjective suspicion indicators confirm that insurers use economic decision models of auditing and suggest that insurers audit with a detection objective in mind. Under both definitions of the dependent variable, the set of predetermined indicators is jointly statistically significant at the 1 percent confidence level. The set of subjective indicators is jointly statistically significant at the 5 percent confidence level when "all audits" is the dependent variable and at the 1 percent confidence level when "investigative audits" is the dependent variable. These results provide evidence that audits, especially investigative audits, are undertaken with a detection objective in mind.[22]

Analysis of Audit Outcomes

The logistic model estimation results support the inference that audits are not undertaken solely for deterrence. Nonetheless, the patterns of audit outcomes examined earlier suggest that auditing may have a deterrent role. We now look for further evidence of a deterrence objective in auditing. We use the predicted probabilities of audits obtained from the logistic model estimation to examine the relationship between the probability that a claim is audited and the outcome of the audit (for claims observed to be audited). As noted previously, if audits are used for detection, then high-opportunism claims will be audited more frequently and buildup will be detected more frequently in these claims. However, if audits are used for deterrence, claims with a greater potential for opportunism will be audited with higher frequency, but the audit outcomes will be random across claims. To examine this distinction, we analyze the relationship between the probability of audit for each claim and the outcome of the audit, if an audit is observed.

The probability of audit is the predicted probability from the logistic models in Table 7 (including the suspicion indicators). To allow for comparison, we construct three

[22] We are more cautious about the results for all audits because when "no plausible explanation for the accident" is treated as a predetermined rather than a subjective indicator, the other subjective indicators are not jointly significant at the 5 percent confidence level. They remain significant at the 1 percent confidence level in the investigative audits model.

TABLE 8
Audit Outcomes by Audit Probability

	All Audits				Investigative Audits			
Probability	Confirmed (%)	Some Elements Doubted (%)	Some Elements Refuted (%)	Total (%)	Confirmed (%)	Some Elements Doubted (%)	Some Elements Refuted (%)	Total (%)
Less Than 0.25	63 (86.3)	8 (11.0)	2 (2.7)	73 (100)	40 (65.6)	15 (24.6)	6 (9.8)	61 (100)
From 0.25 to 0.5	106 (71.1)	35 (23.5)	8 (5.4)	149 (100)	52 (57.1)	35 (38.5)	4 (4.4)	91 (100)
Greater Than 0.5	76 (56.3)	43 (31.9)	16 (11.9)	135 (100)	50 (55.6)	28 (31.1)	12 (13.3)	90 (100)
Total	245 (68.6)	86 (24.1)	26 (7.3)	357 (100)	142 (58.7)	78 (32.2)	22 (9.1)	242 (100)

intervals for the fitted probabilities, for all audits, and for investigative audits. The first interval groups claims with a predicted probability of audit between 0 and 0.25, the second interval groups claims with a predicted audit probability between 0.25 and 0.50, and the third groups those between 0.50 and 1.0. Table 8 shows the relationship between audit probabilities and audit outcomes. A non-statistically significant relationship between the audit outcome and the probability of audit will provide evidence that insurers audit for deterrence, whereas a significant relationship between the audit probability and audit outcome will indicate that insurers are auditing to detect buildup.

Using the estimated model for all audits, 73 of the audited claims were predicted to be audited with probability less than 0.25, 149 were predicted to be audited with probability between 0.25 and 0.50, and 135 were predicted to be audited with probability greater than 0.50. Among the claims in the lowest probability band, 86.3 percent were confirmed by audit, and 13.7 percent had some elements doubted or refuted. Among those in the middle probability band, 71.1 percent were confirmed by audit and 28.9 percent had some elements doubted or refuted. Of those in the highest probability band only 56.3 percent were confirmed by audit, and 43.8 percent had some elements doubted or refuted. The percentages of audited claims not completely confirmed (i.e., doubted or refuted) increased significantly over the audit probability intervals.[23]

Using the predicted probabilities for investigative audits, the percentage of investigated claims confirmed is smaller in all probability bands, and the rate of decline in confirmation percentages is flatter over the probability bands, as compared to all audits. Of the 61 claims that were predicted to be investigated with probability less than 0.25, 65.6 percent were confirmed and 34.4 percent had some elements doubted or refuted. Of the 91 claims predicted to be investigated with probability between

[23] Chi-square test statistic is 21.76 (p value = 0.00).

0.25 and 0.50, 57.1 percent were confirmed and 42.9 percent had elements doubted or refuted. Of the 90 claims predicted to be investigated with probability greater than 0.50, 55.6 percent were confirmed and 44.4 percent had elements doubted or refuted. However, these differences across the audit probability intervals are not statistically significant, and thus the results for investigative audits are consistent with a deterrent role for auditing.[24]

CONCLUSIONS

This article has investigated the role of claims auditing in an automobile insurance market. Our findings reveal that between one-fifth and one-third of claims receive audits. The probability that a claim will be audited increases with the value of the claimed amount. The probability of audit also varies with the potential for opportunism in claiming, as evidenced by sprain claims and tort-eligible claims being audited with greater frequency. Several specific indicators of suspiciousness of a claim were also found to be significantly and positively related to the probability of audit. These patterns are consistent with the use of economic decision models of audit determination by insurers.

Two measures of auditing were used in the analysis, one that counted recorded statement-taking as an audit method (all audits) and one that did not (investigative audits). We took this approach due to the concern that recorded statements may be used by some insurers as a record-keeping device, not an auditing method.[25] While the available data do not permit strong conclusions regarding the validity of making such a distinction, the estimation results are stronger when recorded statements are excluded. Thus, we tended to put more weight on the results obtained when recorded statements were not counted as audits.

The results of analyzing investigative audits show that auditing patterns are consistent with the use of audits for both fraud detection and fraud deterrence. Consistent with a detection objective, subjective characteristics of claims that could only be determined on an individual claim basis were found to be significantly and positively related to the probability that a claim was investigated. However, the fact that less than 10 percent of audited claims had some elements refuted by investigative audits, and more than 40 percent were fully confirmed, is consistent with auditing for deterrence. In addition, while high-opportunism claims were more frequently subjected to investigative audits, the rate of fraud detection among those claims was not significantly greater than for claims investigated with lower probability. This is consistent with auditing for deterrence, under which auditing probabilities will adjust across claims categories to the extent needed to deter fraud or buildup.

The empirical results of this article thus suggest that insurers pursue both detection and deterrent objectives in auditing. However, due to limitations of the data sample, caution must be used in interpreting the findings in this manner. More detailed information on both the timing and sequencing of audit decisions is needed. The impact of auditing on claims withdrawal, on joint claiming decisions (for example, PIP and BIL

[24] Chi-square test statistic is 6.94 (p value = 0.14).

[25] We do not know the identity of any insurer in the data set, nor can we match claims to insurers. Thus we cannot determine patterns of recorded-statement use or verify their purpose by insurer.

claims by a single claimant), and on claiming patterns over time would be useful to analyze the detection versus deterrence benefits of auditing. Finally, analysis of claims data from more than one state and one line of business is needed to verify that the findings of this article extend to the industry as a whole.

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