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Ex-Post Behavior In Insurance Markets

Greg Nini
University of Pennsylvania

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Abstract

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Disciplines

Business | Economics | Public Affairs, Public Policy and Public Administration

EX-POST BEHAVIOR IN INSURANCE MARKETS*

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Greg Nini** *Federal Reserve Board*

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* This is a preliminary proposal based on work with Paul Kofman.

** Division of Research and Statistics, Federal Reserve Board, 20th and C Streets NW, Washington DC, 20551. Telephone: 202-285-0652. Email: gregory.p.nini@frb.gov.

1 Introduction

Insurance markets are proving to be a fruitful area for empirical work on contract theory. Since much of the theoretical work on contracts is motivated by moral hazard and adverse selection, insurance seems a natural product on which to study the impact that private information and unobservable actions have on contract terms and performance. While several theoretical papers incorporate repeated contracting over time (see Chiappori, 2000, for a review), empirical research has yet to fully address the repeated nature of insurance contracting (Chiappori and Heckman, 2002, and Cohen, 2002, are exceptions). Many insurance purchases are quite persistent over time (Nini, 2004, documents significant persistence in auto insurance). With short-term contracts and repeated interactions, ex-post moral hazard becomes important as consumers have strategic incentives to prevent the revelation of potentially costly information. This is particularly true for drivers involved in a auto accident: making a claim provides valuable indemnification yet reveals information that may lead to future premium increases.

A unique contract feature in Australian auto insurance provides an opportunity to identify the importance of ex-post behavior (after an accident happens but before the claim is paid) in insurance markets. Australian auto insurance is partly experienced rated, meaning that claims where the insured is determined to be "at-fault" have an explicit impact on future premiums. Insureds who have an accident are faced with the common tradeoff of reporting the claim and being indemnified or not reporting the claim and saving future premiums. Importantly, insureds reaching the top rating class are given the option to purchase "Rating Protection" against making an at-fault claim. In exchange for a premium, insureds can make a single at-fault claim without facing subsequent premium increases. Roughly one-quarter of the sample population chooses this option, and this paper examines differences in claims outcomes for these two groups of insurance customers.

The first contribution of this paper is to identify an example where additional insurance leads to a marked change in outcomes. Insureds purchasing this Rating Protection have significantly more claims than insureds not purchasing the protection. This result is important since prior research has frequently found at most a small relationship between the amount of insurance purchased (e.g. the size of a deductible) and the probability of a claim. Finding that insureds respond to the incentives provided by contracts restores some credibility to the rationality of the consumer and our economic models used understand behavior.

The more noteworthy contribution of the paper is to document that the significant difference in outcomes appears principally attributable to actions taken after an accident occurs. The data suggest that insureds frequently choose not to make claims for accidents that happen, but this effect is muted by the purchase of Rating Protection. While the positive correlation between Rating Protection and claim frequency is consistent with both adverse selection and ex-ante moral hazard, the empirical results suggest that the driving force for the difference in claim frequency is that insureds without Rating Protection are considerably more likely to hide their accident and not make a claim on the policy. Such behavior is a rational response to the incentives provided by the experience rating system used in Australia. The lack of significant evidence of ex-ante moral hazard or adverse selection is consistent with prior literature on auto insurance that fails to find a positive correlation between claims and the amount of insurance after controlling for observable rating variables.

The impact of under-reporting is first identified by a series of reduced form comparisons of the claim severity distributions and the claim type (at-fault vs. no fault) distributions for insured with and without Rating Protection. Regression results suggest that policies with Rating Protection have significantly smaller claims on average than policies without protection, consistent with policies having Rating Protection having additional small claims. This conclusion is supported by Probit regressions that estimate the likelihood that a policy has a claim of a particular size. The results suggest that policies with Rating Protection are more likely to have small claims (under A$1,000) but no less likely to have large claims (greater than A$5,000). Moreover, non-parametric estimates of the conditional severity distributions confirm the intuition that the differences in average claim amounts is driven by more mass in the left tail of the distribution for policies with Rating Protection. Simply, the data indicate that policies without Rating Protection seem to have fewer small claims than comparable policies with Rating Protection.

Furthermore, the distributional differences are strongest for claims classified as at-fault by the insurance company. Conditional on a claim occurring, policies with Rating Protection are much more likely to have an at-fault claim, and the severity differences are not evident for no fault claims. Combined, the evidence suggests that the observed differences in outcomes are due to significantly more under-reporting by policies without Rating Protection.

In order to explore the implication of under-reporting further, an econometric model of accident frequency and claiming behavior is specified. The observed claim distribution is assumed to be a censored version of the unobservable accident distribution, where the censoring happens stochastically (as in Nelson, 1977). Insureds are assumed to have an unobservable, stochastic threshold below which accidents will not be reported. Consequently, the insurance company only receives claims that are larger than this threshold. The observed mean claim severity is larger than the underlying mean accident severity, and the observed mean claim frequency is less than the underlying mean accident frequency. The unobserved threshold is permitted to vary with the status of Rating Protection, allowing identification of the effect that Rating Protection has on accident frequency, accident severity, and the claiming threshold.

The econometric results suggest that the large increase in claim frequency is driven by policies with Rating Protection having a much lower claiming threshold and slightly larger accident frequency. Policies without Rating Protection engage in significant under-reporting, which results in low claim frequency rates and high average claim severity relative to policies without Protection, who fail to report only the smallest of claims. Incorporating the effect of under-reporting explains over 80 percent of the difference in observed claim frequency and all of the difference in average claim severity. The remaining difference in claim frequency may be attributable to ex-ante moral hazard and/or adverse selection. However, the remaining effect is economically small, especially relative to the impact of ex-post moral hazard.

Section 2 outlines the insurance system in Australia, concentrating on the unique system for setting premiums and option to buy Rating Protection. Section 3 provides pure reduced form results suggesting that under-reporting of small at-fault claims is quite prevalent for insureds without Rating Protection. Section 4 provides a more structural model to uncover the distribution of accident frequency and severity using the observed distribution of claim frequency and severity. Section 5 concludes.

2 Australian Auto Insurance and Data

2.1 Australian Auto Insurance

In Australia, insurance protection for automobile related accidents is provided similarly to many European countries. Coverage is separated into first-party and third-party coverage. The third-party coverage insures a driver against liability created by an at-fault accident that damages another person's property. This coverage is mandatory for all drivers and is provided under a highly regulated pricing scheme. The first-party coverage is optional and typically purchased through a comprehensive policy. Comprehensive coverage insures a driver against loss from damage to the driver's own car resulting from accident, theft, fire, and various other perils.

First-party coverage is priced in a two-stage procedure that adjusts premiums based on the primary driver's rating class and claims experience. A driver's rating class is a function of a set of characteristics related to the driver and the automobile. Among many, the characteristics include the age and gender of the driver, the make and model of the car, and the location where the car is garaged. A base premium is offered as a function of the rating class. The final premium is determined by applying a no claims discount (NCD) to the base premium, where the NCD is an insured specific rating determined by the insured's claim history. All drivers enter the system as a rating 6 and move up or down according to their claim experience. A year without a claim results in a one step improvement in rating (down in the scale), while a claim will result in a two step increase.[1] Compared with rating 6, rating 5 offers a 20 percent premium discount, and each additional step provides an additional 10 percent reduction. Rating 1 drivers receive a 60 percent reduction from the base premium.

Insureds have various contract choices that also affect final premiums. An optional excess (deductible) of A$400 is available, which most insureds choose in order to reduce their premiums. An agreed value endorsement provides coverage up to a pre-specified amount, rather than the market value of the car at time of loss. Other features are available, but they are typically chosen by only a small portion of the insured population.

Most importantly for this study, insureds reaching the top NCD rating (level 1) have the option to purchase Rating Protection that will protect the high rating and corresponding premium discount against one claim that would otherwise cause the rating to increase. Insureds pay an additional premium for this coverage. Moreover, after retaining the top rating for three years without a claim, this coverage is given to all insureds at no additional cost. Insureds with Rating Protection are permitted to make a single at-fault claim without losing their rating 1 status, although a claim does reset the clock measuring time until free Rating Protection is granted.

2.2 Dataset

The dataset is a large cross-section of policies from a single Australian insurance company. The original set is comprised of all comprehensive policies in effect during the

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[1] As will be discussed later, not all claims are treated equally. In general, only at-fault claims result in a NCD rating decrease.

year July 1, 1996 through June 30, 1997. All policies in-force during this year are included in the sample, with in-force policies being active at least some point during the year. The longest policy is one year, so policy have inception dates as early as July 1, 1995 and as late as June 30, 1997. Claims related to these policies are recorded only if they happen during the period July 1, 1996 through June 30, 1997. The data includes the inception date of the policy, so all statistics and econometric tests incorporate the number of days of exposure that the policy is active during the accident period.

Several initial restrictions are made to produce a more homogeneous sample. Only vehicles intended for private use by an individual family are included in the data. This restriction excludes vehicles intended primarily for commercial use by a business. The sample also excludes all leased vehicles, which leaves only vehicles fully owned or privately financed. In Australia, automobile insurance policies have a mandatory excess in addition to the optional A$400 excess. The sample is restricted to all policies with no mandatory excess and $400 voluntary excess.[2]

For each policy, the data includes the set of observable variables used to construct rating classes. These variables include common characteristics know to affect the insurance claim distribution and are separated into variables related to the insured driver and variables related to the insured automobile. The variables include the age and gender of the primary driver, the primary location of the insured driver, the age and value of the insured automobile, and several other variables related to the crashworthiness of the automobile. Table 2 provides a list and brief description of each variable.

The sample is trimmed based on outliers of the continuous variables in the data. The top and bottom 1 percent of the sample is dropped based on the sample percentiles of the continuous variables. Results are qualitatively robust to the exclusion but the quadratic functional forms imposed in the models are more appropriate for the trimmed data.

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[2] This restriction removes a potential source of moral hazard and/or adverse selection.

The data also includes various variables related to the details of the particular policy. Most relevant for the study here, the data includes an indicator that the policyholder purchased Rating Protection. The data also provide the total number of claims made on the policy during the accident period, the total amount of claim payments made related to the claims, and a simple categorization of the type of claim. The claim categories indicate whether the claim was determined to be 'at-fault' or not. An at-fault claim would result in a reduced NCD rating, at least in the absence of Rating Protection. In general, at-fault claims include multiple car accidents where the driver is at least partly to blame (e.g. "insured rear-ended a third party") and all single car accidents regardless of blame where the offender is unknown (e.g. "car damaged while parked").

3 Rating Protection and Under-Reporting

Obviously, the premium rating scheme provides incentives for insureds to reduce the number of claims reported to the insurance company. Since car accidents are generally unobservable to the insurance company, insureds can reduce claims by simply not reporting accidents to the insurer. The cost of not reporting is the forgone indemnification promised by the policy, and the benefit is that the insured maintains the higher rating. As a result, under-reporting should be more prevalent for smaller claims and at-fault claims.

3.1 Unconditional Comparison

Roughly one-quarter of the sample has Rating Protection, and the fraction choosing protection increases with the number of years the insured has a rating 1. Table 1 reports sample summary statistics for insureds with and without Rating Protection. Across the entire sample, policies generate claims with frequency about 9.4 percent per year. However, insureds without Rating Protection have a sample claim frequency of 8.5 percent, and insureds with Rating Protection have a sample frequency of 11.8 percent. This 38 percent increase in claim frequency is statistically different from zero and quite meaningful economically. As will be seen shortly, no other variables have such a large effect on claim frequency.

The lower part of Table 1 presents some summary statistics about the nature of claims across the two categories. Note that the share of claims considered 'at-fault' is larger for policies with Rating Protection. Across the whole sample, the fraction of at-fault claims rises from 63.2 percent to 68.7 percent, which is a statistically significant 8.6 percent (5.5 percentage points) increase in the share of at-fault claims.[3] Since only at-fault claims affect the insured's rating, the incentive to under-report is strongest for these claims, and the evidence suggests that insureds without Rating Protection report less at-fault claims.

The bottom three rows present the sample mean, median, and standard deviation of claim payments. Across the whole sample, policies without Rating Protection have an average claim of A$3,727, and policies with Rating Protection have an average claim of only A$3,048. The mean difference of $679 (18.2 percent) is significantly different from zero at conventional significance levels. Since the cost of not reporting an accident to the insurance company is the forgone indemnification, insureds have more incentive not to report for smaller claim sizes. Consistent with this, policies without Rating Protection have higher average claim costs.

In total, the initial evidence strongly suggests that policies with Rating Protection have significantly more claims, significantly more 'at-fault' claims, and significantly lower average claim costs. All of these results are consistent with under-reporting of smaller, at-fault claims by insureds without protection. As a final note, the large increase in claim frequency dominates the decrease in conditional claim severity so that the sample mean unconditional cost of claims is significantly larger for policies with Rating Protection. Across the whole sample, policies without protection have mean claim costs of A$319, while policies with Rating Protection have mean claim costs of A$360.

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[3] The percent of at-fault claims is larger than 50 percent because single car accidents are considered 'at-fault'.

3.2 Initial Regression Results

One potential explanation for the observed differences in outcomes is observable differences in rating classes across the two groups. Tables 3, 4, and 5 present regression results analogous to the summary statistics above. All regressions use a set of observable explanatory variables constructed from the variables in Table 2. All continuous explanatory variables are standardized by subtracting the sample mean and dividing by the sample standard deviation. Both a linear and a quadratic term are included for all continuous variables. Seven of the eight DISTRICT dummy variables are used in all regressions.

Table 3 provides the estimation results for a claim frequency and claim severity model. The claim frequency model is a probit model where the dependent variable is the number of claims per day. The estimation assumes that the probability of a claim in a single day is constant across days and captured by $\Phi(\beta' X)$, where $\Phi(\cdot)$ is the standard normal CDF. The claim severity model is an OLS model where the dependent variable is the log of the reported claim amount, conditional on the claim being classified as 'at-fault'. All 4,725 at-fault claims are included in the sample.

The results confirm the expectation that the explanatory variables do help explain the distributions of claim frequency and claim severity. However, the effect of Rating Protection remains quite strong. In the frequency regression, the coefficients on RATING PROTECTION are all positive and significantly different from zero. Moreover, Rating Protection increases claim frequency by roughly 3 percentage points across the three years of rating 1, which is an economically significant increase. Similarly, the coefficients on RATING PROTECTION are all negative and significant in the claim severity regression. Policies with RATING PROTECTION have claims that are roughly A$1,000 smaller on average than policies without Rating Protection.

Table 4 provides estimation results for a model of the probability that a claim is classified as at-fault. All reported claims are included in the regression, and the dependent variable is an indicator that the claim is at-fault. While the at-fault likelihood of a particular claim is related to some of the explanatory variables, the effect of Rating Protection remains quite strong. The point estimates suggest that the increase is roughly 5 percentage points for policies in their first or second year of rating 1 and nearly 10 percentage points for policies in their third year.

Finally, Table 5 presents two probit models for the likelihood that a particular claim is of a certain size. The first model uses all claims, and the dependent variable is an indicator that the claim is less than A$1,000. The second model uses all claims greater than A$1,000, and the dependent variable is an indicator that the claim is greater than A$5,000. In both models, few of the explanatory variables significantly affect the probability of a small claim or the conditional probability of a large claim. The notable exception is the presence of Rating Protection. The results of the first model suggest that Rating Protection roughly doubles the likelihood that a particular claim is below A$1,000. However, Rating Protection is not significantly related to the conditional probability that a claim is above A$5,000. The coefficients are negative, but they insignificantly different from zero and relatively small in magnitude. The combined results strongly suggest that the reduction in average claim severity for policies with Rating Protection is driven by a relative increase in the number of small claims.

As final corroborating evidence, Figure 1 plots the residuals from the claim severity regression presented in Table 3. The regression includes a dummy variable indicating that the policy has Rating Protection, so the sample mean of residuals conditional on Rating Protection is zero. However, the shape of the conditional residual distribution provides evidence about the nature of the underlying claims distribution. To that end, the Figure 1 provides a histogram and fitted kernel distribution for the residuals conditional on Rating Protection. Two differences are noticeable. First, the claims distribution for policies with Rating Protection has higher variance. Second, the claims distribution for policies with Rating Protection is more left-skewed than the distribution for policies without Rating Protection. When controlling for both Rating Protection and the number of years with rating 1, the differences in variance and skewness are significantly different from zero at a 5 percent level. Again, these results are consistent with under-reporting by insureds without Rating Protection, which generates the differences in skewness. The next section provides a more general model that can generate such observable differences.

4 A Model of Claiming

4.1 Econometric Set-Up

The goal is to generate consistent estimates of the effect that Rating Protection has on the unobserved accident frequency and severity distribution, using only information in the observed claim frequency and severity distributions. With under-reporting of accidents, the observed claim distribution is a censored version of the accident distribution. The Nelson (1977) model of censoring with an unobserved, random threshold provides a natural model for the observed claim distribution. Dionne and Gagne (2000) use this model for insurance claim payments and find evidence of significant under-reporting. The modeling contribution here is to permit under-reporting to affect both the observed severity and frequency distributions.

Suppose the probability of an accident occurring on any given day is given by p_A. The probability p_A is modeled as in a standard probit model, $p_A = \Phi\left(\beta_A' X\right)$, where $\Phi(\bullet)$ is a standard normal CDF, X is a vector of explanatory variables, and β_A is a vector of coefficients. In a given span of d days, the probability of no accident occurring is $(1-p_A)^d$, and the probability of an accident occurring is $1-(1-p_A)^d$, denoted $p_A(d)$.

Conditional on an accident occurring, the unobserved severity of the accident is determined by a draw from a lognormal distribution, $\ln(S) \sim \mathrm{N}\left(\beta_S' X, \sigma_S\right)$, where β_S is a vector of severity coefficients, and σ_S is the standard deviation of the log of the accident amount. The log-normality assumption is imposed because first-party auto claims do not have fat tails and the distribution has proved to fit the data before (Kofman and La, 1998).

Finally, each insured is assumed to have an unobservable threshold below which accidents will not be reported. The threshold is modeled as a draw from a lognormal distribution, $\ln(T) \sim \mathrm{N}(\beta_T^{'} X, \sigma_T)$, where β_T is a vector of severity coefficients, and σ_T is the standard deviation of the log of insureds' thresholds. Random variables S and T are permitted to have non-zero correlation, but both are assumed independent of A.

The observed data is the couple (I_C, C), where I_C is an indicator that the policy had a claim payment, and C is the total claim payments made on the policy. Since a claim is reported if and only if it is larger than the threshold, we have the following model for the observed data:

$$(I_C, C) = \begin{cases} (0,0) & \text{if } A = 0 \text{ or } (A = 1 \text{ and } S \le T) \\ (1, C) & \text{if } A = 1 \text{ and } S = C \text{ and } T < C \end{cases}$$

The probability of the observed data can be written as a function of the distributions of the underlying fundamental random variables (A, S, T).

$$\begin{aligned} &\Pr[(I_C, C) = (0,0)] = \Pr(A = 0) + \Pr(A = 1) \cdot \Pr(S \le T) \\ &\Pr[(I_C, C) = (1, C)] = \Pr(A = 1) \cdot \Pr[\ln(S) = \ln(C) \mid S > T] \end{aligned} \tag{1}$$

First, given the independence of A, the observed claim severity distribution can be derived as in Maddalla (1983):

$$\begin{aligned} \Pr[\ln(C) \mid I_C = 1] &= \frac{\Pr[\ln(S) = \ln(C), \ln(S) > \ln(T)]}{\Pr[\ln(S) > \ln(T)]} \\ &= \frac{\Pr[\ln(S) = \ln(C)] \cdot \Pr[\ln(T) < \ln(C) \mid \ln(S) = \ln(C)]}{\Pr[\ln(S) > \ln(T)]} \end{aligned}$$

The denominator is the unconditional probability that an accident is larger than the insured's threshold. By the normality assumption $\ln(T) - \ln(S)$ is distributed normally with mean $(\beta_T - \beta_S)^{'} X$ and variance $\sigma_T^2 + \sigma_S^2 - \sigma_{ST}$, and the probability in the denominator is given by

$\Phi\left(\frac{(\beta_S - \beta_T)' X}{\sqrt{\sigma_T^2 + \sigma_S^2 - \sigma_{ST}}}\right) =$. Again by the joint normality assumption on $\ln(S)$ and $\ln(T)$, the conditional probability of $\ln(T)$ in the numerator is normal with mean $\beta_T X + \frac{\sigma_{ST}}{\sigma_S^2}(\ln(C) - \beta_S X)$ and variance $\sigma_T^2 - \frac{\sigma_{ST}^2}{\sigma_S^2}$. The probability in the numerator then becomes $\phi\left(\frac{\ln(C) - \beta_S' X}{\sigma_S}\right)\Phi\left(\frac{\ln(C) - \beta_T' X - \frac{\sigma_{ST}}{\sigma_S^2}(\ln(C) - \beta_S X)}{\sqrt{\sigma_T^2 - \frac{\sigma_{ST}^2}{\sigma_S^2}}}\right)$. Combining the numerator an denominator yields:

$$\Pr[\ln(S) = \ln(C) \mid S > T] = \frac{\phi\left(\frac{\ln(C) - \beta_S' X}{\sigma_S}\right)\Phi\left(\frac{\ln(C) - \beta_T' X - \frac{\sigma_{ST}}{\sigma_S^2}(\ln(C) - \beta_S X)}{\sqrt{\sigma_T^2 - \frac{\sigma_{ST}^2}{\sigma_S^2}}}\right)}{\Phi\left(\frac{(\beta_S - \beta_T)' X}{\sqrt{\sigma_T^2 + \sigma_S^2 - \sigma_{ST}}}\right)}. \qquad (2)$$

The unconditional probability that an accident happens but is not reported is given by 1 minus the unconditional probability that an accident is larger than the threshold:

$$\Pr(S \le T) = 1 - \Phi\left(\frac{(\beta_S - \beta_T)' X}{\sqrt{\sigma_T^2 + \sigma_S^2 - \sigma_{ST}}}\right). \qquad (3)$$

Finally, using $\Pr(A = 1) = p_A(d) = 1 - [1 - \Phi(\beta_A' X)]^d$, all the components of (1) are specified and the log-likelihood of a particular observation is given by:

$$\ln L\left(\beta_A, \beta_S, \beta_T, \sigma_S, \sigma_T, \sigma_{ST} \mid I_C, C, X, d\right) =$$

$$(1 - I_C)\log\left\{\left[1 - \Phi\left(\beta_A^{'} X\right)\right]^d + \left[1 - \left[1 - \Phi\left(\beta_A^{'} X\right)\right]^d\right]\left[1 - \Phi\left(\frac{\left(\beta_S - \beta_T\right)^{'} X}{\sqrt{\sigma_T^2 + \sigma_S^2 - \sigma_{ST}}}\right)\right]\right\}$$

$$+ (1 - I_C)\log\left\{1 - \left[1 - \Phi\left(\beta_A^{'} X\right)\right]^d\right\}$$

$$+ (1 - I_C)\log\left\{\frac{\phi\left(\frac{\ln(C) - \beta_S^{'} X}{\sigma_S}\right)\Phi\left(\frac{\ln(C) - \beta_T^{'} X - \frac{\sigma_{ST}}{\sigma_S^2}\left(\ln(C) - \beta_S X\right)}{\sqrt{\sigma_T^2 - \frac{\sigma_{ST}^2}{\sigma_S^2}}}\right)}{\Phi\left(\frac{\left(\beta_S - \beta_T\right)^{'} X}{\sqrt{\sigma_T^2 + \sigma_S^2 - \sigma_{ST}}}\right)}\right\}.$$

Maximum likelihood estimation results in estimates of the parameters β_A, β_S, and β_T, including parameter estimates on the variables related to Rating Protection.

4.2 Results

Table 6 provides the maximum likelihood estimates of the model presented above. Estimation uses the entire sample of 176,913 observations, and the likelihood function is maximized using the Newton-Raphson method with numerical derivatives. Starting values for the accident severity and accident frequency coefficients are taken from the simpler models presented in Table 3. Starting values for the threshold coefficients were all set to zero, but results are qualitatively robust to alternative starting values. All the models include dummy variables for 7 of the 8 DISTRICT variables, and the residual standard deviation was permitted to vary with the number of years of Rating Protection. The point estimates (standard errors) for the standard deviation of accident severity are .966 (.040), .949 (.036), and .926 (.024) for one year, two year, and three years with Rating Protection, respectively. Point estimates (standard errors) for the threshold standard deviation are .681 (.128), .649 (.121), and .620 (.136). The estimated conditional correlation between accident severity and the unobserved threshold is .223, with a standard error of .146, suggesting an unobserved factor that is positively correlated with both accident severity and the unobserved claiming threshold.

The results of the claiming model indicate a significant amount of unreported claims in the data. The unconditional model implied probability of an accident is 9.2 percent, 8.1 percent, and 7.8 percent for insureds with one year, two years, or three years of the top rating. Table 3 indicated that the comparable claim frequencies are 6.5 percent, 5.8 percent, and 5.1 percent. The difference is due to the censoring of small claims due to under-reporting. The estimated threshold coefficients imply an unconditional mean threshold of A$865, A$960, and A$1,083, based on the three intercepts. Given the accident severity distribution, such large thresholds result in many claims not being reported. The estimated accident severity coefficients confirm that the claim severity estimates in Table 3 are upward biased estimates of accident costs. The unconditional mean cost of accidents is A$3,487, A$3,198, and A$2,918, which are A$375, A$534, and A$705 less than the mean claim costs. The increase in the bias is due to censoring being more likely for insureds with a Rating 1 for more years.

Controlling for censoring significantly reduces the impact that Rating Protection has on expected accident frequency. While insureds with Rating Protection have claims roughly 3 percentage points more often, the coefficient estimates in Table 6 indicate that accidents happen only roughly .5 percentage points more often. While still significantly greater than zero, the economic impact is relatively small and dramatically smaller than the impact on claims. The model estimates suggest that over 80 percent of the increase in claims for insured with Rating Protection is due to the under-reporting of claims for insureds without Rating Protection.

Figure 2 provides an illustration of the impact that under-reporting has on the resulting claims distribution. Along the horizontal axis is the amount of an accident, chart depicts the estimated probability that the claim is not reported to the insurance company. For insureds with Rating Protection, the likelihood of under-reporting falls off very quickly, essentially reaching zero by accidents larger than A$250. For insureds without Rating Protection, however, accidents around A$250 are not reported nearly 60 percent of the time. Even one-fifth of accidents costing A$1,000 are not reported. Given the large mass of the accident distribution falling under A$2,000, it is not surprising that insureds with Rating Protection have many more claims.

The estimated coefficients on the remaining variables show several interesting patterns. Few of the threshold coefficients are significantly different from zero, so the likelihood of claim censoring doesn't vary much with these other characteristics. Consequently, the sign and size of many of the coefficients in the frequency and severity equations are similar in the accident (Table 6) and claiming (Table 3) models. The amount of insurance (AMT_INSURE) and the age of the vehicle (AGE_VEH) are the two exceptions. The threshold is estimated to be negatively related to the amount of insurance and positively related to the age of the vehicle. Figures 3 and 4 illustrate the effects that various levels of AMT_INSURE and AGE_VEH have on the probability a claim versus the probability of an accident. In Figure 3, AMT_INSURE reduces the mean threshold, which in turn causes the probability of an accident not being reported to fall from over 35 percent to under 15 percent. The large decrease in the under-reporting causes the claim frequency probability to approach the accident frequency probability. For small values of insurance, under-reporting reduces the claim probability by over 3.5 percentage points, but for large insurance values, under-reporting reduces the claim probability by only 1 percentage point. Similarly, Figure 4 shows that the likelihood of under-reporting increases significantly with the age of the car, from roughly 5 percent for young vehicles to over 20 percent for older vehicles. Consequently, the claiming probability shows a much more marked decrease with vehicle age than does the accident probability.

5 Conclusions

Empirical work trying to identify adverse selection and moral hazard has had mixed results at best, particularly when applied to auto insurance data. However, empirical research suggests that fraud in auto insurance is easily identified and economically significant. The results here suggests that another ex-post action, the under-reporting of claims, is also prevalent in insurance markets and deserves further theoretical and empirical research.

The collection of empirical work on information problems indicates that the ability to affect outcomes after the resolution of uncertainty is at least as important as ex-ante information differences or ex-ante moral hazard. Perhaps this is not surprising for insurance related to infrequently occurring events. For example, consider the effect of Rating Protection on the ex-ante incentives of a driver in the sample considered here. Driving less cautiously may reduce the cost of effort, but the relative benefit is only the expected reduction in future premiums due to the Rating Protection. While the future premium reductions may be substantial, it is unlikely that reduced effort will dramatically increase the probability of a claim. Even with a generous 10 percentage point increase in the probability of a claim, the expected premium reduction is only one-tenth of the actual premium reduction. This significantly reduces the relative benefit of driving less cautiously and likely reduces the impact of ex-ante moral hazard. Of course, after an accident occurs, the full premium reduction is the cost faced by insureds without Rating Protection, providing much more incentive to under-report accidents.

The impact of ex-post moral hazard likely has larger welfare implications for insurance related to more productive assets. When an insured fails to report a claim, the insured loses a valuable source of financing to invest in a depreciating asset (e.g. fixing the broken fender on a car or repairing a roof damaged by a hurricane). In the presence of financing frictions, under-reporting creates an important negative externality in that the asset remains less productive. Such effects may be important in the insurance of corporate assets such as plant and equipment.

Ex-post behavior deserves more attention in the theoretical literature on contracting. The ability to affect outcomes after the resolution of uncertainty but before payoffs happen is likely part of many contracting situations. Long-term lending agreements are certainly signed in anticipation that some uncertainty will be realized before repayment occurs. To the extent that the borrower can affect the likelihood of repayment after resolution of uncertainty, an analogous situation of ex-post moral hazard arises. An understanding of optimal contracting in such a situation will further guide our understanding of the contracts and outcomes we see in practice.

6 References

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Table 1. Unconditional Comparison of Policies With and Without Rating Protection

The table provides a descriptive comparison of policies with and without rating protection. 'One Year', 'Two Years', and 'Three Years' indicates the number of years the policyholder has been at the top rating class. 'Exposure Years' is the aggregate number of days expressed at an annual frequency. 'Claim Frequency' is the sample average number of claims of claims per year, expressed as a percentage. 'At-Fault Percentage' is the sample average share of total claims where the driver faces a rating downgrade. The 'At-Fault Severity' sample statistics are conditional on an at-fault claim being made.

	One Year		Two Years		Three Years	
	No Rating Protection	With Rating Protection	No Rating Protection	With Rating Protection	No Rating Protection	With Rating Protection
Number of Policies	63,100	14,208	40,220	14,941	31,344	13,100
Exposure Years	27,411	6,150	16,998	7,265	13,714	6,122
Claim Frequency (percent)	9.3	13.2	8.2	11.3	7.5	11.0
Number of Claims	2,557	813	1,389	819	1,022	674
At-Fault Percentage (percent)	64.2	70.0	63.7	68.9	60.1	66.9
At-Fault Severity Mean (A$)	3,888	3,271	3,624	3,197	3,446	2,581
At-Fault Severity Median (A$)	2,634	2,061	2,417	1,763	2,345	1,623
At-Fault Severity St Dev (A$)	4,316	3,573	3,584	5,216	3,457	3,117

Table 2. Conditioning Variables

The table provides a description and summary statistics for all of the conditioning variables available in the data. The sample is the entire set of 176,913 policies representing 77,760 years of exposure. The sample has been limited by removing policies falling in the upper and lower 1 percent of the distribution of the continuous variables. 'Std' represents that sample standard deviation.

Variable	Description	Mean	Std	Min	Max
Driver Characteristics					
AGE_INS	Age of primary driver at inception of policy.	41.4	13.4	24.0	80.0
DISTRICT	Aggregation of geographic postal codes defined by insurer.	8 Dummy Variables			
FEMALE	Indicates primary driver is a female.	0.45			
FINANCED	Indicates privately financed vehicle, with alternative a fully owned vehicle.	0.11			
AGE_POL	Consecutive number of years the policy has been in force with the insurer.	2.0	2.5	0.0	13.0
Automobile Characterisitc					
ENGSIZE	Engine size, in thousands of cubic cylinders.	2.6	1.0	1.2	5.0
CATPTS	Measure of the crash worthiness of the vehicle. (Higher is more expensive.)	10.2	3.5	3.0	24.0
AMT_INSURE	Value, in A$10,000, of the automobile.	1.1	0.8	0.2	4.7
AGE_VEH	Age, in years, of vehicle at policy issuance.	8.9	4.9	1.0	25.0
Policy Characteristics					
DAYS	Number of days the policy was in force during the accident period.	160	102	1	365
PREMIUM	Total premium charged on the policy.	419	118	179	918

Table 3. At-Fault Claim Frequency and Claim Severity Regressions

The table provides the estimation results for a claim frequency and claim severity model. The claim frequency model is a probit model where the dependent variable is the number of at-fault claims per day. The estimation assumes that the probability of a claim in a single day is constant across days and captured by $\Phi\left(\beta' X\right)$, where $\Phi(\bullet)$ is the standard normal CDF. The sample has 176,913 observations representing over 28 million days. The model is estimated by maximum likelihood, and estimated standard errors are in parentheses. '**' ('*') indicates coefficients significantly different from zero at a 1 (5) percent confidence level. All continuous explanatory variables are standardized by subtracting the sample mean and dividing by the sample standard deviation. 7 of the 8 DISTRICT dummy variables are included. The 'Estimated Probability' column reports the model implied probability of a claim in a year. For the intercepts, the predicted values assume all other variables are zero. For the three Rating Protection variables, the predicted values use the estimated coefficient plus the appropriate intercept. The other two indicator variables use the ONE YEAR INTERCEPT without rating protection. For the continuous variables, the 'Minus 1' ('Plus 1') column shows the predicted values for a one standard deviation decrease (increase) in the variable relative to the mean, again using the ONE YEAR INTERCEPT without rating protection. The continuous variable predicted values incorporate both the linear and quadratic effects.

The claim severity model is an OLS model where the dependent variable is the log of the reported claim amount, conditional on the claim being classified as 'at-fault'. All 4,725 at-fault claims are included in the sample. The regression has an R-squared of .43. The 'Estimated $A' columns show expected claim severity amounts computed analogously to the predicted values from the claim frequency model. The predicted values use the estimated residual variance of 0.91.

Table 3. Initial Claim Frequency and Claim Severity Regressions (continued)

	Claim Frequency			Claim Severity		
	Probit	Estimated Probability		OLS	Estimated $A	
	Coefficient	Minus 1	Plus 1	Coefficient	Minus 1	Plus 1
ONE YEAR INTERCEPT	-3.5630 **	6.5		7.923 **	3,861	
	(0.0010)			(0.049)		
TWO YEARS INTERCEPT	-3.5950 **	5.8		7.889 **	3,732	
	(0.0010)			(0.052)		
THREE YEARS INTERCEPT	-3.6258 **	5.1		7.859 **	3,623	
	(0.0011)			(0.055)		
RATING PROTECTION x ONE YEAR	0.1112 **		9.7	-0.283 **		2,910
	(0.0009)			(0.045)		
RATING PROTECTION x TWO YEARS	0.0999 **		8.3	-0.322 **		2,798
	(0.0010)			(0.050)		
RATING PROTECTION x THREE YEARS	0.1259 **		8.2	-0.425 **		2,525
	(0.0011)			(0.057)		
FEMALE	-0.0106 **		6.2	-0.037		3,721
	(0.0008)			(0.038)		
FEMALE x AGI_INS	0.0202 **	5.9	7.1	-0.005	4,046	3,685
	(0.0004)			(0.022)		
FEMALE x AGI_INS^2	0.0063 **			-0.042 *		
	(0.0004)			(0.018)		
MALE x AGI_INS	0.0200 **	5.9	7.1	-0.039 *	4,063	3,670
	(0.0004)			(0.020)		
MALE x AGI_INS^2	0.0063 **			-0.012		
	(0.0003)			(0.016)		
FINANCED	0.0800 **		8.7	0.021		3,945
	(0.0008)			(0.042)		
AGE_POL	-0.0146 **	6.8	6.2	-0.030	4,010	3,719
	(0.0004)			(0.022)		
AGE_POL^2	0.0030 **			-0.008		
	(0.0003)			(0.012)		
ENGSIZE	0.0100 **	6.6	6.3	-0.047 *	3,908	3,815
	(0.0004)			(0.019)		
ENGSIZE^2	-0.0156 **			0.035 *		
	(0.0004)			(0.018)		
CATPTS	0.0146 **	6.1	6.9	0.042 *	3,765	3,960
	(0.0003)			(0.017)		
CATPTS^2	0.0008 **			-0.017		
	(0.0002)			(0.009)		
AMT_INSURE	0.0152 **	6.3	6.7	0.010	3,821	3,902
	(0.0007)			(0.037)		
AMT_INSURE^2	-0.0065 **			0.001		
	(0.0002)			(0.011)		
AGE_VEH	-0.0149 **	7.3	5.7	0.015	3,948	3,777
	(0.0006)			(0.031)		
AGE_VEH^2	-0.0174 **			-0.037 **		
	(0.0003)			(0.014)		

Table 4. At-Fault Likelihood Regressions

The table provides probit estimates for the likelihood of a claim being classified as at-fault. The sample includes all 7,274 claims, and the dependent variable is an indicator that the claim is at-fault. The probit model is estimated by maximum likelihood, and standard errors are in parentheses. '**' ('*') indicates coefficients significantly different from zero at a 1 (5) percent confidence level. 7 of the 8 DISTRICT dummy variables are included. The 'Implied Probability' columns reported fitted probabilities computed as in Table 3.

Table 4. At-Fault Claim Regressions (continued)

	Probit	Implied Probability	
	Coefficient	Minus 1	Plus 1
ONE YEAR INTERCEPT	0.292 **	61.5	
	(0.056)		
TWO YEARS INTERCEPT	0.293 **	61.5	
	(0.058)		
THREE YEARS INTERCEPT	0.175 **	56.9	
	(0.062)		
RATING PROTECTION x ONE YEAR	0.169 **		67.8
	(0.054)		
RATING PROTECTION x TWO YEARS	0.138 *		66.7
	(0.058)		
RATING PROTECTION x THREE YEARS	0.219 **		65.3
	(0.065)		
FEMALE	0.042		63.1
	(0.044)		
FEMALE x AGI_INS	0.133 **	54.1	68.5
	(0.026)		
FEMALE x AGI_INS^2	0.057 *		
	(0.024)		
MALE x AGI_INS	0.095 **	55.2	67.5
	(0.023)		
MALE x AGI_INS^2	0.066 **		
	(0.021)		
FINANCED	0.145 **		66.9
	(0.050)		
AGE_POL	-0.050 *	62.4	60.6
	(0.025)		
AGE_POL^2	0.026		
	(0.015)		
ENGSIZE	0.062 **	59.1	63.8
	(0.022)		
ENGSIZE^2	-0.049 *		
	(0.020)		
CATPTS	-0.020	61.9	61.1
	(0.019)		
CATPTS^2	0.009		
	(0.010)		
AMT_INSURE	0.058	60.2	62.8
	(0.043)		
AMT_INSURE^2	-0.023		
	(0.013)		
AGE_VEH	0.067	59.4	63.5
	(0.036)		
AGE_VEH^2	-0.014		
	(0.016)		

Table 5. At-Fault Severity Regressions

The table provides probit estimates for two percentiles of the claim severity distribution. The 'Small Claim Likelihood' model includes all 4,725 at-fault claims, and the dependent variable is an indicator that the claim is less than A$1,000. The probit model is estimated by maximum likelihood, and standard errors are in parentheses. '**' ('*') indicates coefficients significantly different from zero at a 1 (5) percent confidence level. The 'Conditional Large Claim Likelihood' model includes only the 3,844 claims larger than A$1,000, and the dependent variable is an indicator that the claim is larger than A$5,000. 7 of the 8 DISTRICT dummy variables are included. The 'Implied Probability' columns reported fitted probabilities computed as in Table 3.

Table 5. Severity Percentile Regressions (continued)

	Small Claim Likelihood			Conditional Large Claim Likelihood		
	Probit	Implied Probability		Probit	Implied Probability	
	Coefficient	Minus 1	Plus 1	Coefficient	Minus 1	Plus 1
ONE YEAR INTERCEPT	-1.063 **	14.4		-0.508 **	30.6	
	(0.081)			(0.083)		
TWO YEARS INTERCEPT	-1.097 **	13.6		-0.615 **	26.9	
	(0.086)			(0.086)		
THREE YEARS INTERCEPT	-1.077 **	14.1		-0.655 **	25.6	
	(0.092)			(0.092)		
RATING PROTECTION x ONE Y	0.407 **		25.6	-0.074		28.0
	(0.071)			(0.076)		
RATING PROTECTION x TWO Y	0.548 **		29.2	-0.031		25.9
	(0.078)			(0.087)		
RATING PROTECTION x THREE	0.605 **		31.8	-0.165		20.6
	(0.089)			(0.105)		
FEMALE	0.059		15.8	0.008		30.9
	(0.061)			(0.063)		
FEMALE x AGI_INS	0.053	12.2	16.8	0.087 *	27.8	33.5
	(0.035)			(0.038)		
FEMALE x AGI_INS^2	0.048			-0.005		
	(0.029)			(0.031)		
MALE x AGI_INS	0.096 **	12.4	16.7	-0.001	31.2	30.0
	(0.033)			(0.032)		
MALE x AGI_INS^2	-0.001			-0.017		
	(0.026)			(0.027)		
FINANCED	-0.063		13.0	0.035		31.8
	(0.070)			(0.069)		
AGE_POL	0.048	13.2	15.6	-0.017	31.6	29.6
	(0.036)			(0.037)		
AGE_POL^2	0.004			-0.013		
	(0.019)			(0.023)		
ENGSIZE	0.057	13.9	14.9	-0.004	31.8	29.4
	(0.031)			(0.032)		
ENGSIZE^2	-0.033			-0.031		
	(0.029)			(0.031)		
CATPTS	-0.068 *	15.9	13.0	0.019	30.2	30.9
	(0.027)			(0.028)		
CATPTS^2	0.003			-0.008		
	(0.015)			(0.015)		
AMT_INSURE	0.064	13.4	15.4	0.030	30.3	30.8
	(0.060)			(0.061)		
AMT_INSURE^2	-0.021			-0.023		
	(0.018)			(0.019)		
AGE_VEH	0.011	13.9	14.9	-0.024	33.9	27.4
	(0.050)			(0.051)		
AGE_VEH^2	0.011			-0.069 **		
	(0.022)			(0.024)		

Table 6. Accident Frequency, Accident Severity, and Claiming Model

The table provides the maximum likelihood estimates of the model presented in Section 4. Estimation uses the entire sample of 176,913 observations. The likelihood function is maximized using the Newton-Raphson method with numerical derivatives. Standard errors are in parentheses. '**' ('*') indicates coefficients significantly different from zero at a 1 (5) percent confidence level. 7 of the 8 DISTRICT dummy variables are included. Point estimates (standard errors) for the standard deviation of accident severity are .966 (.040), .949 (.036), and .926 (.024) for one year, two year, and three years with Rating Protection, respectively. Point estimates (standard errors) for the threshold standard deviation are .681 (.128), .649 (.121), and .620 (.136). The estimated conditional correlation between accident severity and the unobserved threshold is .223, with a standard error of .146.

Table 6. Accident Frequency, Accident Severity, and Claiming Model (continued)

	Accident Frequency	Accident Severity	Threshold
	Coefficient	Coefficient	Coefficient
ONE YEAR INTERCEPT	-3.4675 **	7.690 **	6.505 **
	(0.0010)	(0.030)	(0.399)
TWO YEARS INTERCEPT	-3.5016 **	7.620 **	6.700 **
	(0.0011)	(0.022)	(0.330)
THREE YEARS INTERCEPT	-3.5122 **	7.550 **	6.820 **
	(0.0012)	(0.018)	(0.514)
RATING PROTECTION x ONE YEAR	0.0200 **	0.035	-1.742 **
	(0.0009)	0.145	(0.342)
RATING PROTECTION x TWO YEARS	0.0138 **	0.020	-1.586 **
	(0.0010)	0.099	(0.265)
RATING PROTECTION x THREE YEARS	0.0182 **	0.015	-1.925 **
	(0.0012)	0.119	(0.442)
FEMALE	-0.0182 **	0.043	-0.145
	(0.0008)	0.036	(0.106)
FEMALE x AGI_INS	0.0255 **	0.038	0.139
	(0.0005)	0.075	(0.141)
FEMALE x AGI_INS^2	0.0059 **	-0.055	-0.098
	(0.0004)	0.048	(0.086)
MALE x AGI_INS	0.0189 **	-0.049 *	0.252
	(0.0004)	0.023	(0.186)
MALE x AGI_INS^2	0.0024 **	-0.017	-0.058
	(0.0004)	0.077	(0.106)
FINANCED	0.0775 **	0.027	-0.104
	(0.0009)	0.049	(0.588)
AGE_POL	-0.0111 **	0.009	-0.189 *
	(0.0005)	0.012	(0.092)
AGE_POL^2	0.0005 *	-0.005	0.079
	(0.0003)	0.057	(0.094)
ENGSIZE	0.0020 **	-0.049 *	0.033
	(0.0004)	0.022	(0.121)
ENGSIZE^2	-0.0025 **	0.036 *	-0.019
	(0.0004)	0.020	(0.059)
CATPTS	0.0124 **	0.066 *	0.037
	(0.0004)	0.030	(0.138)
CATPTS^2	0.0004 *	-0.010 *	-0.034
	(0.0002)	0.005	(0.044)
AMT_INSURE	0.0075 **	0.059 *	-0.285 **
	(0.0008)	0.032	-(0.119)
AMT_INSURE^2	-0.0020 **	-0.010 *	0.124 *
	(0.0002)	-0.005	(0.059)
AGE_VEH	-0.0025 **	-0.043	0.288 *
	(0.0007)	0.027	(0.149)
AGE_VEH^2	-0.0244 **	-0.008	-0.234 *
	(0.0003)	0.018	-(0.127)

Figure 1. Severity Regression Residuals

The figure displays residuals from the claim severity regression presented in Table 3. The grey bars are a histogram of sample residuals and the black shaded area is the CDF of a fitted nonparametric kernel density estimate. The top panel shows residuals from the policies without rating protection and the bottom panel shows residuals from policies with rating protection. The regression includes an indicator of rating protection, so the sample mean of the residuals is zero for both groups.

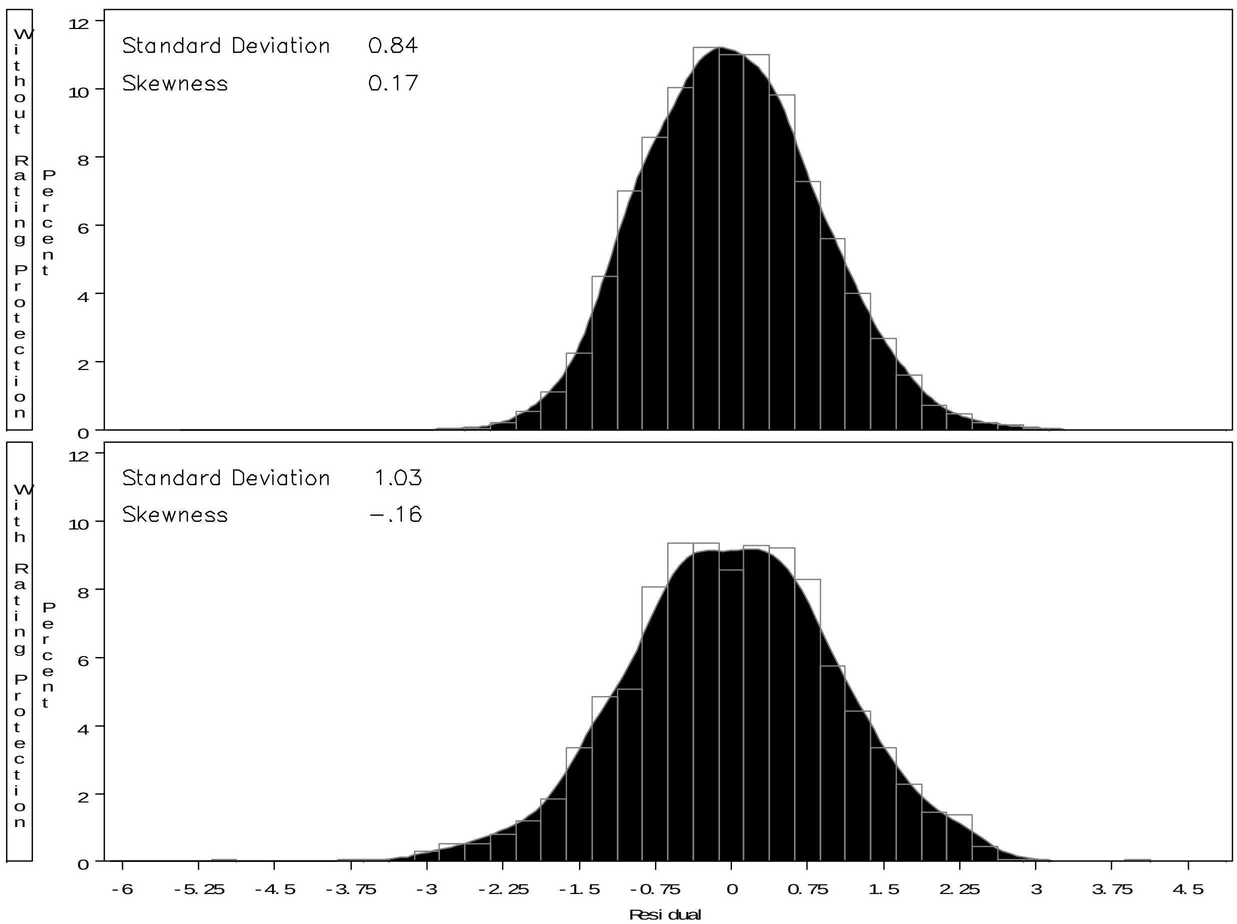

Figure 2. Fitted Conditional Probabilities of Not-Reporting an Accident

The charts show fitted probability that a particular accident is not reported to the insurance company, based on the model estimates shown in Table 6. The horizontal axis is the size of an accident measured in A$, and the vertical axis is measured in percent. The estimates are based on an insured with Rating 1 for one year and sample mean values for all other variables. The estimated standard deviation of accident severity is .966, and the estimated standard deviation of the threshold is .681. The estimated conditional correlation between accident severity and the unobserved threshold is .223. The effect of rating protection is based on the estimated coefficient assuming one year of protection.

Figure 2. Fitted Conditional Probabilities of Not-Reporting an Accident (continued)

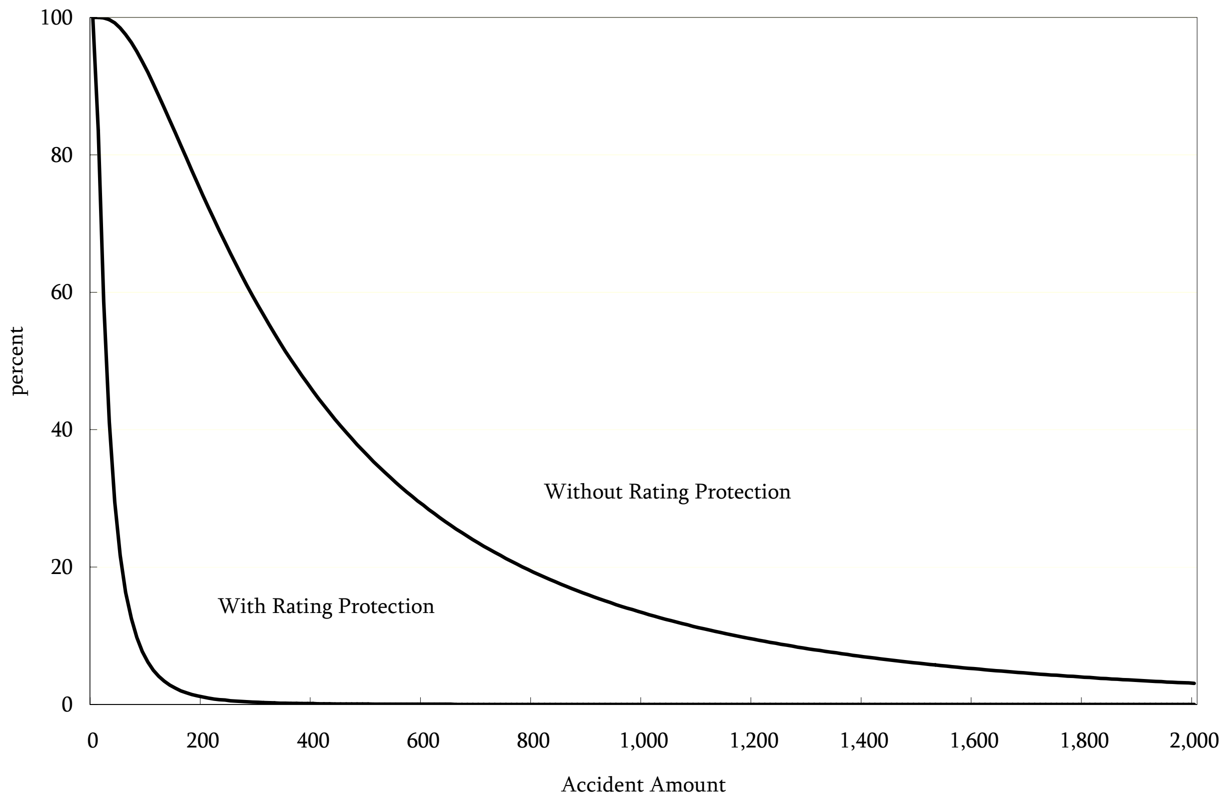

Figure 3. Comparative Statics for Fitted Model – Amount of Insurance (AMT_INSURE)

The charts show fitted expected values based on the model estimates shown in Table 6. The horizontal axis is measured in units of standard deviations from the mean. The top panel shows the expected accident severity and the expected threshold (measured in A$ on the left axis) along with the unconditional probability that an accident is not reported (measured on the right axis). The estimates are based on an insured with Rating 1 for one year, no rating protection, and sample mean values for all other variables. The estimated standard deviation of accident severity is .966, and the estimated standard deviation of the threshold is .681. The estimated conditional correlation between accident severity and the unobserved threshold is .223. The bottom panel shows the estimated accident probability and the estimated claim probability, which is generated as the product of the accident probability and one minus the probability of censoring.

Figure 3. Comparative Statics for Fitted Model – Amount of Insurance (continued)

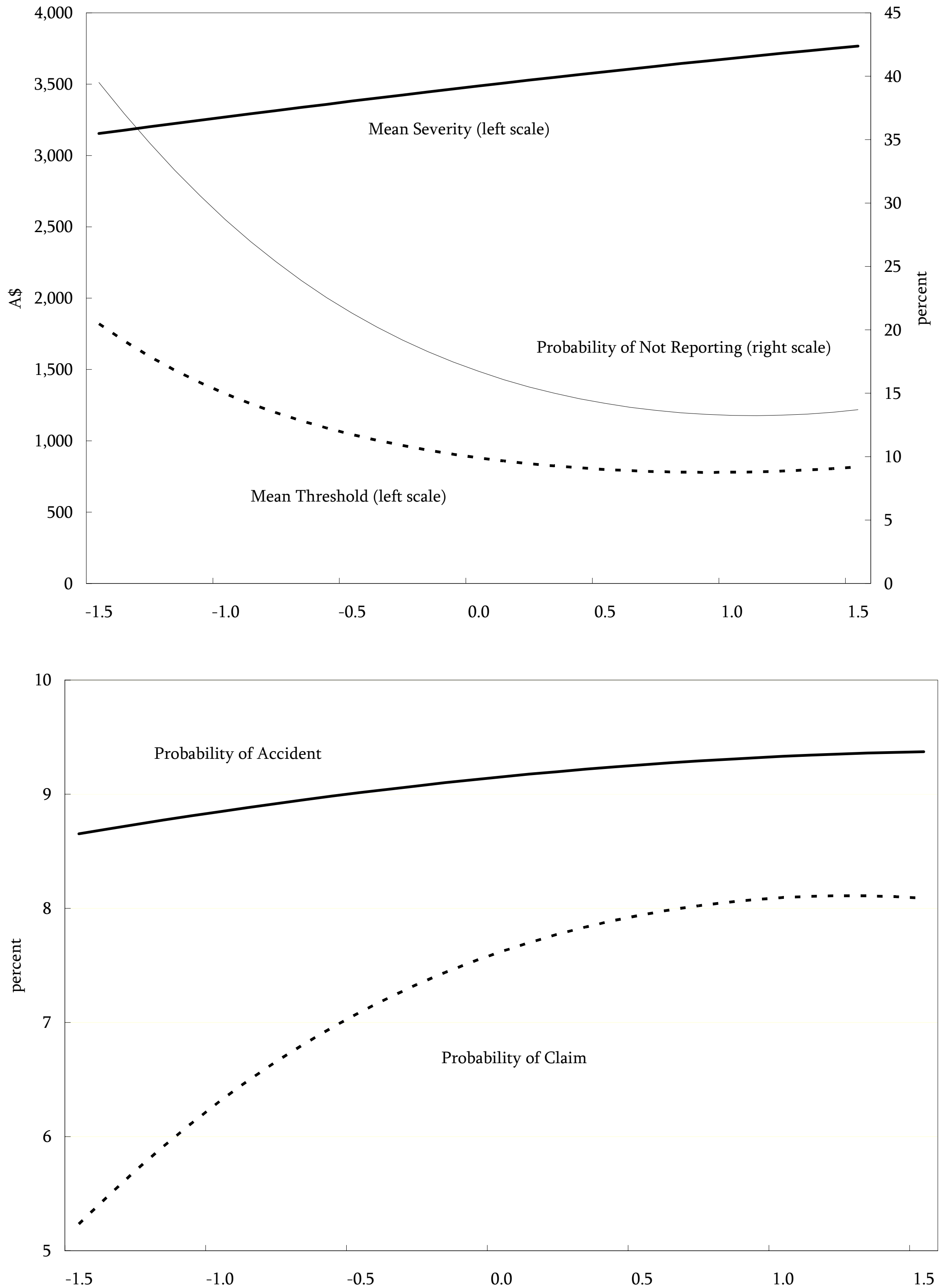

Figure 4. Comparative Statics for Fitted Model – Age of Vehicle (AGE_VEH)

The charts show fitted expected values based on the model estimates shown in Table 6. The horizontal axis is measured in units of standard deviations from the mean. The top panel shows the expected accident severity and the expected threshold (measured in A$ on the left axis) along with the unconditional probability that an accident is not reported (measured on the right axis). The estimates are based on an insured with Rating 1 for one year, no rating protection, and sample mean values for all other variables. The estimated standard deviation of accident severity is .966, and the estimated standard deviation of the threshold is .681. The bottom panel shows the estimated accident probability and the estimated claim probability, which is generated as the product of the accident probability and one minus the probability of censoring.

Figure 4. Comparative Statics for Fitted Model – Age of Vehicle (continued)