MEASURING FRAUD IN INSURANCE INDUSTRY: THE CASE OF AUTOMOBILE INSURANCE IN TAIWAN

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Abstract

By conducting an extensive exploration on claim data, this paper attempts to investigate the fraud problem in Taiwan automobile physical damage insurance. Based on the different claim patterns between data in calendar year and policy year, excess claims are significantly identified in the last month of policy year. Censored regression provides robust estimation concerning the sources of the fraud payment.

Key Words: automobile insurance, collusion, insurance fraud, excess claim, moral hazard

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I. Introduction

Insurance fraud is a hot topic in insurance industry recently. In general, insurance fraud can be defined as an attempt to obtain compensation for the alleged accident that never happened or was unrelated to the accident and as an attempt on the part of the claimant to inflate the damages for which compensation is being sought. Insurance fraud could increase risk costs to raise insurance premium so that the consumers who demand for insurance might not be able to buy it. Although fraud problems mainly belong to practical issues, academic studies gradually pay attention to this subject because of the negative effect of fraud on insurance pricing and the efficiency of the insurance market.

Numerous studies on automobile insurance fraud have been conducted since 1990's. For example, Weisberg and Derrig (1991, 1992, 1995, 1996) and Derrig, Weisberg and Chen (1994) investigate fraud and abuse in Massachusetts automobile insurance claims; Caron and Dionne (1999) and Dionne and Belhadji (1996) examined similar problems using Canadian data. Cummins and Tennyson (1992) found that there were significant effects of attitudes toward fraud on automobile liability claims. Furthermore, Carroll, Abrahamse, and Vaiana (1995), Abrahamse and Carroll (1998) and Carroll and Abrahamse (2001) analyzed the soft-injury claim patterns across the states which executed different types of insurance system to estimate excess claims and in the recent study they found that approximately 42% of reported soft-injury claims in the dollar-threshold and tort states were for nonexistent or preexisting injuries. Other papers such as Derrig and Ostaszewski (1995), Weisberg and Derrig (1998) and Brockett et al., (1998) try to develop proper techniques identifying fraudulent claims or doing fraud classification. Moreover, Moreno et al. (2006) demonstrated that bonus-malus contracts might be able to contain an incentive against fraud.

Using a unique data set, this paper attempts to investigate the fraud problem in Taiwan by econometric analysis and to provide robust estimation of the magnitude of fraud payment. Since excess or fraud claims are not easy to observe directly, we will use data exploration and econometric model to identify excess claims. The focus of this study is on the variability of claim frequency (and payment) for various automobile insurance policies. The major hypothesis testing would base on the difference of claim pattern between calendar year and policy year.

Theoretically, claim frequencies or payments of automobile physical loss are supposed to distribute evenly in every month. If plot claim data by calendar month on a diagram, we would expect to see little difference among months for a specific year. However, the sale of automobile insurance policy in Taiwan heavily relies on agents associated with car dealer. As a common custom, some insurance agents would encourage policyholders to file a claim that does not actually occur just before the end of insurance policy. In this way, the covered car might get new paint or unnecessary repair with new parts. Although Taiwan adopts bonus-malus system in automobile insurance market, policyholders would obtain higher claim coefficient and hence pay high premium for the next policy year, a large portion of the insured still do not care or even do not know (never told) exactly how the system works. Therefore there is incentive for agents to take advantage of insurer to increase the revenue of auto shops. Based on the process described above, we would expect a high peak of claim frequency appeared in the last month of policy year.

In Taiwan, there are three major types of coverage for vehicle damage insurance: comprehensive form A, comprehensive form B, and moving collision coverage (form C). The comprehensive form A policy, sold with compulsory increasing per-claim deductibles, covers all perils. Comprehensive form B policy, sold with increasing per-claim deductibles or zero deductible, covers the same risks as form A but excludes vandalism and unknown perils. The moving collision policy, sold with no deductibles, covers only two cars collision peril.

Compared with the transaction costs to file an excess claim for various form of insurance coverage, we would expect moving collision coverage (form C) to have less incentive because two cars collision is needed. Among all the forms, Comprehensive form B without deductible contains the highest incentive for the insured to file fraud claims.

After data illustration, the study will perform the regression analysis by following the methodology in Dionne and Gagne (2001). The key issue is that for various coverage and deductibles, the reservation amounts of filing a claim are different. This creates data censored problem. As proposed in Dionne and Gagne (2001), the modified method by Nelson(1977), Maddala(1983) will be used.

In the next section, we briefly interpret the dataset and explore the claim data. Section 3 illustrates methodology we adopt including empirical models and variables. Empirical estimations are conducted in Section 4. Finally, Section 5 concludes this research.

II. Data Exploration

The data used in this study are unique. We obtained the data sets that contain entire private automobile vehicle damage insurance policies and claims in Taiwan for years 2003 to 2005. Through merging the data sets of policy and claim, we search out the whole claim data for policy years 2003 and 2004. The data sets, including the characteristics of policyholder, vehicle, claim driver and contract types, are provided by Taiwan Insurance Institute, a semi-official organization responsible for publishing insurance statistics and financial data of insurers.

A first look of the data confirms our hypothesis of fraudulent claims. Figure 1 and figure 2 show that four different forms of contract have similar claim frequencies and payments (about 7-10%) at various calendar months. However, if we plot the claim frequencies and payments in terms of policy month in Figure 3 and 4 respectively, there are significantly high peaks (from 20% to 40%) appeared in the last policy months. Among them, as expected, form C policy has the lowest claim ratio while form B policy with no deductible has highest claim ratio in the last month of policy year.

[Insert Fig. 1 to Fig. 4]

We use the nonparametric Kolmogorov-Smirnov and Wilcoxon tests to compare the claim ratios in the last policy month with that of other policy months. Table 1 confirms that the ratios of claim frequency in the last policy month are significantly different from that in other policy months for all types of coverage. As far as the claim payment is concern, as Table 2 shows, claim ratios of payment are significantly higher in the last policy month than in other policy months except for form C policy. Therefore we can reject the null hypothesis that claim ratios in the last policy month have the same distribution as in the other policy months.

[Insert Table 1, Table 2]

Due to the largest difference of claim ratios between the last month and other policy month, we would specially focus on form B policy in this study.

However, the abnormal claims might be caused by the bonus hunger behavior, indicating that consumers report one accident only after accumulating several small losses to reduce transaction costs and to avoid negative influence on driving record. Hence we check the claims pattern of those cases having more than two claims in one policy year. The Kolmogorov-Smirnov and Wilcoxon tests cannot reject the hypotheses that the claim patterns are the same for different claim frequency in one policy year. Moreover, we find that the average claim payment per claim is relatively lower in the last policy month. To further check up the difference of average claim amount between the last policy month and other policy months, we confirms that average claim amount between the last policy month and other policy months are significantly diverse.

III. Methodology and Variables

In this section, we analyze the behavior of insurance fraud on form B policy. Firstly, our objective is to identify the characteristics of automobile insurance policies that might induce excess claims in the last policy month. PROBIT model is used to estimate the effect of insured factors on dependent variable, a binary variable indicating the occurrence of claim filed in the last policy month. The empirical model may be expressed as

$$\textbf{\textit{Prob.}}\ (Clm12_i = 1) = \alpha' X_i + \mu_i \tag{1}$$

where $Clm12_i$ is a dummy variable that equals 1 if individual i filed a claim in the last policy month and 0 otherwise; X_i is a vector of regressors; α' is a vector of parameters; μ_i is a disturbance in our setup.

The following variables are used in our model (the subscript i is omitted):

District 1-District22: a set of dummy variables taking the value 1 if the automobile is registered in j district, j = 1,2,…,22, and 0 otherwise.

Company 1- Company 16: a set of dummy variables taking the value 1 if the policy is from insurance company j, j = 1,2,…,16, and otherwise.

Exhaust: cubic capacity of the automobile with an incremental unit of 1,000cc.

Clmcoef: the claim coefficient, an indicator of past driving record.

Car_age: the age of the insured automobile in years.

Dr_age: the age of the driver who filed a claim.

Dr_female: a dummy variable that equals 1 if the driver is female and 0 otherwise.

Dr_married: a dummy variable that equals 1 if the driver is married, and 0 otherwise.

Identical: a dummy variable that equals 1 if the driver is the same as policyholder, and 0 otherwise.

Renew: a dummy variable that equals 1 if the policy renews in the same insurance company next policy year and 0 otherwise. We don't consider whether the policy renews in the same form.

Poyr03: a dummy variable that equals 1 if the claim is in 2003 policy year, and 0 otherwise.

Deductible: a dummy variable that equals 1 if the policy is with deductible and

0 otherwise. There are several types of deductible. Considering the consistence of coverage and large samples, we exclude other types of deductibles except increasing per-claim deductible.

Table 3 and 4 depict the descriptive statistics of the data. When analyzing claim data on form B policy with both deductible and no deductible, we eliminate the policies with straight deductible and just retain those with increasing per-claim deductibles for consistency in coverage. Increasing per-claim deductibles are NT$ 3000, 5000, and 7000 respectively. It is worth noting that the figures in Table 4 do not reveal the true gender distribution. The proportions of males in form B policy with no deductible and deductible are 55.89% and 60.53%, but the proportions of male drivers in claim data are 29.49% and 37.00% respectively, indirect testimonial to the fact that most automobile insurance policies are purchased under the name of a female family member. This phenomenon is easily explained by the difference in gender coefficients for males and females. The nature of this phenomenon is confirmed through the variables of ***Dr_married*** and ***Identical*** in Table 4, which shows more than 75% of claim drivers are married and less than 50% of claim drivers are the same person as policyholder in all categories. This is lead to the fact that for a given age, males have a higher pricing coefficient than females. Furthermore, average car age is close to zero, representing that most automobiles are new.

[Insert Table 3, 4]

IV. Empirical Results

In PROBIT regression approach, the estimated results are presented in Table 5. We run three different subsets, namely form B with no deductible, form B with deductible and, form B (coverage bias corrected) to understand whether there exist different effects for varied coverage.

[Insert Table 5, 6]

When considering the individual characteristics of the drivers, it seems that three variables, ***Dr_age***, ***Dr_female*** and ***Identical***, play important role in explaining the claim behavior in the last policy month. The coefficient of drivers' age is significantly positive. Under the same condition, the increase of driver's age could raise the possibility of claim filed in the last policy month. Cohen (2005) tested the predictions of adverse-selection models using data from automobile insurance market in Israel and found that a positive coverage-accidents correlation exists only for policyholders with enough years of driving experience, consistent with the possibility of policyholders' learning about their risk type. In light of the similar finding, older drivers might have enough experience to collude with car dealers.

Although the proportion of the male driver is higher as described above, car dealers might use policyholders' information to file claims in the last policy month for operational convenience. Therefore the probability of female drivers filing claims in the last policy month could increase obviously, supporting our conjecture. On the other hand, the probability of the drivers who are the same as policyholders filing claims in the last month of policy year significantly increases on form B policy with no deductible, consistent with the argument of operational convenience. We further take into account interaction term between ***Dr_female*** and ***Identical*** in the specification, and the result shows that the probability of the last policy month claims filed by the female drivers who are the same as policyholders statistically significantly increases.[1] Therefore, all of these results consistently support our inference providing the indirect evidence of insurance fraud in the last month of policy year.

The factors of car type are measured by car age (***Car_age***) and cubic capacity of the automobile (***Exhaust***). The coefficient of car age is significantly negative in all regression models, representing that the newer cars would probably easy to have accidents in the last policy month. As Table 3 shows, most cars are new and the owners of new car would usually buy physical damage insurance policies. In the case of collusion, the result is reasonable. On the other hand, the results imply that the policyholders with new car whose claim coefficient could almost be zero would have more incentives to defraud. Regarding the variable of ***Exhaust***, the coefficients of all data sets are significantly negative. The automobiles with larger displacement are usually more expensive and could denote the wealth of the car owners. Hence, we may conclude that wealthy people have less incentive to file claims in the last policy month.

Moreover, the features of contract are taken into account with ***Clmcoef***, ***Renew*** and ***Deductible***. Claim coefficient is calculated from claim reports in the past three years and hence may indicate the risk type of policyholder. We find that the probability of claim is positively correlated with claim coefficient but the probability of the claim filed in the last policy month is negatively correlated with claim coefficient.[2] The policyholders who have higher bonus-malus coefficient are high

[1] The coefficients associated with ***Dr_female*** on form B policy with no deductible, form B policy with deductible and form B policy corrected coverage bias when ***Identical*** = 1 are 0.0748, 0.0541 and 0.0683 with standard error 0.0074, 0.0164 and 0.0068 respectively. Therefore, they are significantly different from zero at 1% confidence level.

[2] We run the PROBIT model and consider dependent variable, a binary variable indicating the occurrence of the fact that at least one claim is filed during the contract. The estimated result is showed in Table 6.

risk drivers and have ever filed claims before. For this reason, past claims might have satisfied the policyholders' need with loss indemnity, hence they have less incentive to deceive in the last policy month. Although bonus-malus system might be able to contain an incentive against fraud in theory, in the case of new car, policyholder's claim coefficient is usually zero, and one claim in policy year has no effect on raising claim coefficient. In addition, most of the policyholders who file one claim only in a policy year would be advantageous compared with opportunity cost. Therefore, the policies with lower claim coefficient would have higher probability to file a claim.

The regression results also reveal the fact that the contracts renewed in the same company in the next policy year would also have higher probability to file claim in the last policy month. The intuition behind this phenomenon is the competition in the automobile insurance market. Car agents might compete each other by providing better service in terms of encouraging fraud claim in the last month of policy year to attract policyholders renew their contracts and then gain the commissions in the next year.

Due to the fact that most consumers prefer automobile insurance policies of form B with no deductible, we may conclude that the probability of claim filed in the last policy month significantly decline if the policy is with deductible from the result on form B policy corrected coverage bias.

Finally, most of the coefficients associated with the district in which the automobile is insured are not significant, indicating that there are no differences among districts in terms of the drivers' behavior. But several company effects are statistically significant, showing that there are significant differences in the way some insurers settle the claims.

V. Conclusions

The purpose of this paper is to measure automobile insurance fraud in Taiwan insurance industry. After the exploration of automobile physical damage insurance claim data, we find that claim ratios of frequency and payment are significantly higher in the last policy month than in other policy months, especially for the form B policy. We consider it as a form of ex post moral hazard or opportunistic insurance fraud.

The special competition environment for car dealers and automobile insurance companies provide the intuition of fraud claim. By offering the sale of automobile and automobile insurance simultaneously, car dealers have more incentives to collude with customers to file fraudulent claims to gain feasible interests. In this situation, it seems that insurers are the victims. However, honest customers are the true victims and will be forced to pay higher insurance premium in the future. The demand for vehicle damage insurance would be affected in such situation.

By focusing on form B policy in Taiwan automobile insurance market, we provide statistical analysis and find that the distributions of claim data in terms of policy month do contain signals of fraud behavior. Further improvement on product design and claim monitor system are needed.

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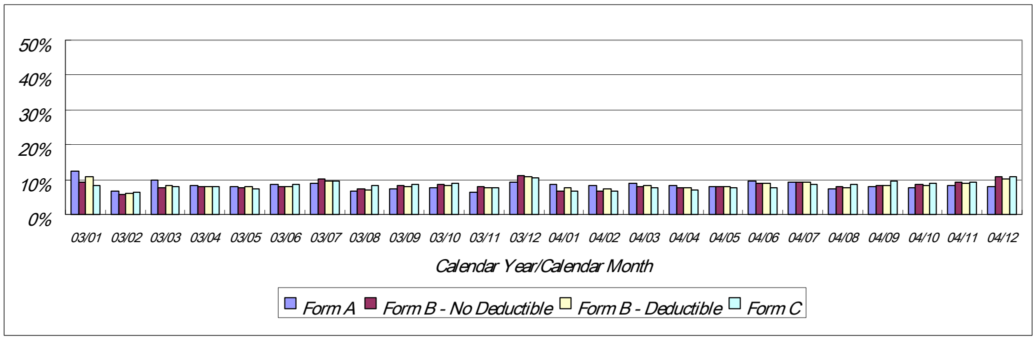

Figure 1. Monthly share of total claim frequencies in 2003 and 2004 calendar years

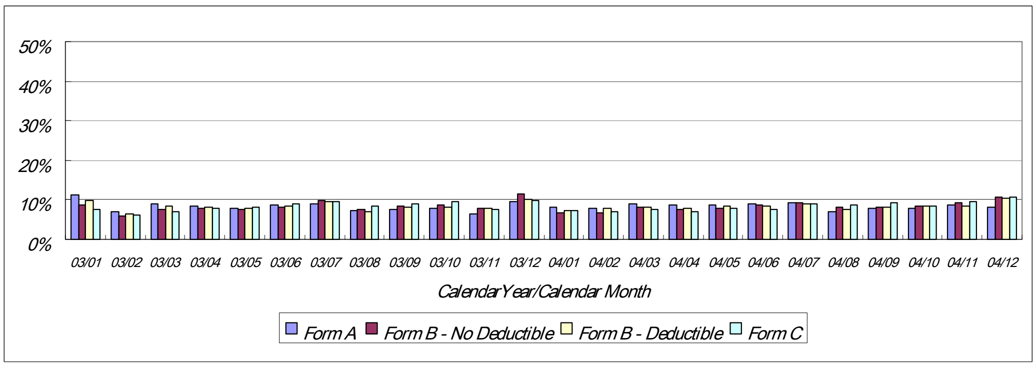

Figure 2. Monthly share of total claim payments in 2003 and 2004 calendar years

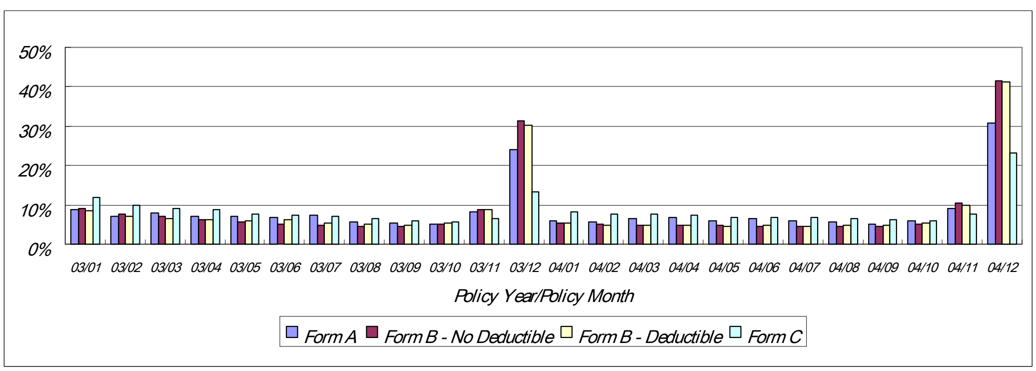

Figure 3. Monthly share of total claim frequencies in 2003 and 2004 policy years

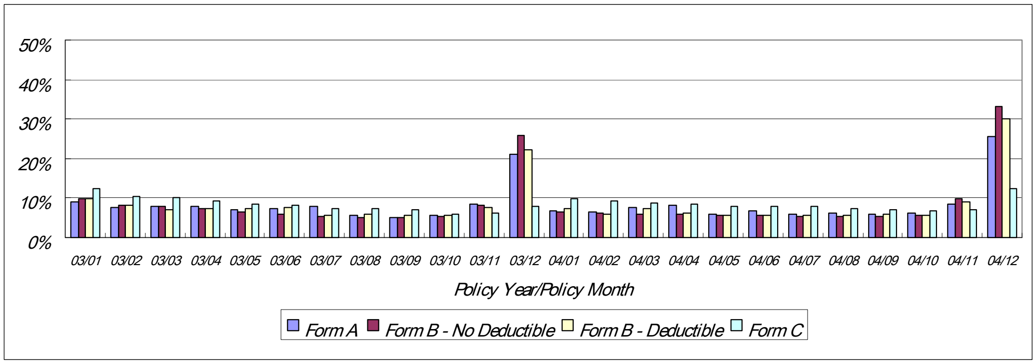

Figure 4. Monthly share of total claim payments in 2003 and 2004 policy years

Table 1. Shift in the last policy month ratios of claim frequency

	Form A	Form B – No Deductible	Form B - Deductible	Form C
Kolmogorov-Smirnov Test				
KSa	1.354006	1.354006	1.354006	1.354006
P-value	0.0511	0.0511	0.0511	0.0511
Wilcoxon Two-Sample Test				
Z	2.2461	2.2456	2.2456	2.2456
P-value	0.0247	0.0247	0.0247	0.0247

Table 2. Shift in the last policy month ratios of claim payment

	Form A	Form B – No Deductible	Form B - Deductible	Form C
Kolmogorov-Smirnov Test				
KSa	1.354006	1.354006	1.354006	0.738549
P-value	0.0511	0.0511	0.0511	0.6465
Wilcoxon Two-Sample Test				
Z	2.2456	2.2456	2.2456	1.2011
P-value	0.0247	0.0247	0.0247	0.2297

Table 3. Descriptive statistics of the continuous variables

	Form B - No Deductible N=176345				*Form B - Deductible* N=40334				*Form B - Coverage Bias Corrected* N=207212			
Variable	Mean	Standard Deviation	Minimum	Maximum	Mean	Standard Deviation	Minimum	Maximum	Mean	Standard Deviation	Minimum	Maximum
Exhaust	1.86	0.63	0.50	47.07	2.09	0.83	0.60	79.05	1.88	0.66	0.50	79.05
Clmcoef	-0.06	0.15	-2.00	1.60	-0.06	0.21	-0.60	2.20	-0.06	0.16	-2.00	1.60
Car_age	0.81	1.42	0.00	16.00	1.45	2.01	0.00	15.00	0.88	1.52	0.00	16.00
Dr_age	36.80	10.49	18.00	90.00	38.52	10.14	18.00	90.00	37.01	10.47	18.00	90.00

Table 4. Frequency of the major dummy variables

	Form B - No Deductible N=176345		*Form B - Deductible* N=40334		*Form B - Coverage Bias Corrected* N=207212	
Variable	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
Clm12	68,442	38.81	15,133	37.52	81,300	39.24
Dr_female	77,770	44.10	15,918	39.47	89,975	43.42
Dr_married	142,284	80.69	30,256	75.01	166,113	80.17
Identical	81,658	46.31	18,235	45.21	96,044	46.35
Renew	39,682	22.50	15,177	37.63	50,525	24.38
Poyr03	47,017	26.66	13,984	34.67	57,678	27.84
Deductible	0	0.00	40,334	100.00	31,755	15.32

Table 5. Binomial PROBIT regressions on the claim filed in the last month of policy year

Variable	*Form B - No Deductible*		*Form B - Deductible*		*Form B - Coverage Bias Corrected*	
Intercept	-5.4692	-5.4924	5.3825	5.3567	5.4243	5.3821
	(567.1154)	(567.7932)	(1269.2350)	(1269.8570)	(1267.9130)	(1270.3880)
Dr_age	0.0015 ***	0.0015 ***	0.0019 ***	0.0019 ***	0.0017 ***	0.0017 ***
	(0.0003)	(0.0003)	(0.0007)	(0.0007)	(0.0003)	(0.0003)
Dr_female	0.0440 ***	0.0198 **	0.0240 *	0.0125	0.0388 ***	0.0140
	(0.0071)	(0.0098)	(0.0146)	(0.0200)	(0.0065)	(0.0090)
Dr_married	0.1478 ***	0.1482 ***	0.1530 ***	0.1458 ***	0.1480 ***	0.1477 ***
	(0.0094)	(0.0093)	(0.0200)	(0.0199)	(0.0086)	(0.0086)
Car_age	-0.0819 ***	-0.0816 ***	-0.0659 ***	-0.0658 ***	-0.0787 ***	-0.0785 ***
	(0.0026)	(0.0026)	(0.0037)	(0.0037)	(0.0023)	(0.0023)
Exhaust	-0.0556 ***	-0.0551 ***	-0.1367 ***	-0.1362 ***	-0.0679 ***	-0.0674 ***
	(0.0056)	(0.0056)	(0.0098)	(0.0098)	(0.0051)	(0.0051)
Clmcoef	-0.1468 ***	-0.1451 ***	-0.1478 ***	-0.1475 ***	-0.1359 ***	-0.1345 ***
	(0.0238)	(0.0238)	(0.0336)	(0.0336)	(0.0206)	(0.0206)
Renew	0.0023	0.0021	0.0942 ***	0.0941 ***	0.0190 ***	0.0189 ***
	(0.0077)	(0.0077)	(0.0143)	(0.0143)	(0.0070)	(0.0070)
Identical	0.0362 ***		0.0183		0.0336 ***	
	(0.0073)		(0.0148)		(0.0067)	
*Dr_female*Identical*		0.0550 ***		0.0666 ***		0.0543 ***
		(0.0107)		(0.0228)		(0.0099)
Deductible					-0.0350 ***	-0.0340 ***
					(0.0087)	(0.0087)
Poyr03	-0.2593 ***	-0.2593 ***	-0.2286 ***	-0.2285 ***	-0.2515 ***	-0.2515 ***
	(0.0077)	(0.0077)	(0.0150)	(0.0150)	(0.0070)	(0.0070)
22 district and 16 company dummies	-	-	-	-	-	-
Observations Used	176,345	176,345	40,334	40,334	207,212	207,212
Log Likelihood	-113049.9079	-113048.7919	-24741.8452	-24738.3533	-132698.7650	-132696.1342

Notes: Standard errors in parenthesis. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 6. Binomial PROBIT regression on claim filed during contract

Variable	*Form B - Coverage Bias Corrected*
Intercept	-0.0951
	(0.6775)
Age	0.0018 ***
	(0.0002)
Female	0.0359 ***
	(0.0047)
Married	-0.0370 ***
	(0.0071)
Car_age	-0.0556 ***
	(0.0014)
Exhaust	-0.0402 ***
	(0.0033)
Clmcoef	0.7077 ***
	(0.0131)
Deductible	-0.0844 ***
	(0.0056)
Poyr03	-0.6232 ***
	(0.0043)
23 district and 19 company dummies (estimates suppressed)	-
Number of observations	501,853
Log Likelihood	-262947.6945

Notes: Standard errors in parenthesis.

*** Significant at the 1 percent level. ** Significant at the 5 percent level.

* Significant at the 10 percent level.