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EMPIRICAL ANALYSIS OF MORAL HAZARD:

A STUDY OF A VEHICLE INSURANCE TAX REFORM

Sherzod Yarmukhamedov – VTI

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Keywords: vehicle insurance, moral hazard, traffic safety, tax reform

JEL Codes: C33, C54, D82, H20, L51

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1. INTRODUCTION

Information asymmetries arise in the insurance industry when an insurer cannot observe all the relevant information about the insured in order to make a proper risk classification when setting the premiums. This leads to several problems. For instance, high-risk drivers are more likely to purchase high-insurance coverage (adverse selection), and drivers who have purchased insurance may be expected to devote less effort to preventing accidents (moral hazard). The distortive incentive effects of insurance may also affect driver behavior and lead to increased social costs of traffic accidents and to improper premium setting. Therefore, thoroughly addressing the problem of asymmetric information is essential from both social and business perspectives.

The insurance literature predicts the presence of a positive correlation between insurance coverage and risk (Rothschild and Stiglitz, 1976), which may reflect both adverse selection and moral hazard. Efficient risk classification ensures premiums which result in no correlation between coverage and risk. However, in the real world there are certain factors such as the type of insured service, institutional factors, rate regulation etc. that impede efficiency in risk classification (Saito, 2006; Dionne et al., 2012). An empirical test of correlation between coverage and risk can reveal whether there is a problem of asymmetric information in the insurance market. Several studies take different approaches to this, where Dionne and Gagne(2002), Israel(2004), Weisburd(2010), Cohen and Dehejia(2004), Dionne et al.(2004b) and Dunham(2003) find the presence of asymmetric information, whereas others, such as Saito(2006), Dionne et al.(2004a), Chiappori and Salanie(2000), Abbring et al.(2003), are unable to establish such a presence.

The major reason for the occurrence of either moral hazard or adverse selection is that driver behavior is private information, i.e. it is difficult for insurers to observe. One way to mitigate the problem is to use deductibles and coinsurance schemes[1]. On the one hand, deductibles provide incentives for cautious driving by inducing a driver to partially cover the financial consequences of

[1] In coinsurance schemes, the costs of losses are shared between insurer and insured according to the conditions stated in the contract. For instance, if a coinsurance scheme is 70/30, then the insurer covers 70 percent of costs, while the remaining 30 percent is the responsibility of the insured. In contrast, in a partial insurance coverage scheme (deductible) the insured pays a predetermined amount of money irrespective of the amount of loss, whereas the rest is the responsibility of the insurer.

carelessness. On the other hand, deductibles may also lead to exaggeration of the actual size of the losses, i.e. actual losses exceed at least the amount of the deductible, which leads to fraudulent claims (Schmidt, 1961). Besides, Li et al. (2007) show that a choice of zero deductible is associated with high frequency of claims. If moral hazard causes exaggeration of the size of losses, then coinsurance schemes may alleviate the problem. Experience rating is another widely used insurance instrument to encourage careful driving (Dionne et al., 2004b). Such schemes increase the efficiency of risk classification by providing additional information to the insurer about the risk level of the driver, which diminishes the moral hazard problem. Conversely, experience rating may encourage claim underreporting behavior because each claim results in higher premiums in the next period.

A main problem of the insurance literature on asymmetric information is insufficient empirical research that distinguishes moral hazard from adverse selection. Cross sectional data used across many studies does not allow separation of moral hazard effects from adverse selection. Dionne et al.(2004b) argue that this failure emanates from imprecise modeling of the dynamic process between contract choice and insurance claims. In contrast to many previous studies, our paper uses a unique data set from the largest insurance company in Sweden for the period 2006-2010, which makes it feasible to model dynamic features of insurance contracts. In this way, it is possible to keep track of the contract choice and claims of individuals. Given such uniqueness of data, the purpose of this study is to address two questions: (1) How has an external cost shock in the form of a tax reform affected the choice of contract with respect to coverage? (2) How has the change in the choice of contract influenced the probability of claims? More specifically, first, we expect that an exogenous increase in premiums generated by a tax reform will induce drivers to reduce the level of insurance coverage, so that the demand for low insurance coverage will increase. Second, reducing the level of insurance will lead to lower premiums as the extent of damages that is covered by each type of insurance is lessened. Then a driver will bear more cost responsibility than prior to a switch, resulting in more careful driving and maintenance of a vehicle. Therefore, we argue that if reduction in insurance coverage leads to fewer claims, then this result might be attributable to the reduction of ex ante moral hazard (Dionne et al., 2012).

The exogenous cost shock can be described in the following way. The government of Sweden has been considering transferring costs of people injured in traffic accidents from social insurance to vehicle insurance. The responsibility for compensating income losses and rehabilitation costs resulting from road traffic accidents would then be transferred to vehicle insurance companies. According to the present regulations, the costs of personal injuries resulted from traffic accidents are partially covered by social insurance, whereas material damages are the responsibility of vehicle insurance companies. The proposal was to be implemented in two steps. The first step was implemented on July 1, 2007 by introducing a 32 percent tax on the basic insurance (third-party) premium. This was intended to partially cover traffic-related accident costs at the outset financed by taxes. The second step was intended to completely transfer the responsibility for traffic-related accident costs from social insurance to vehicle insurance. However, the second step has not been implemented.

Our database contains insurer information on individual characteristics (id, date of birth, sex, place of residence, number of household members), vehicle characteristics (registration number, brand, model, production year, mileage) and contract details (premium, contract duration, type of coverage, number of claims, damages awarded). Based on the choice of contract type in different periods, drivers are classified into three groups, i.e. switcher, stable and reverse-switcher. A panel has been constructed according to a special sample selection procedure and two models are used to analyze the consequences of the tax reform. In the first model, we analyze the propensity for making a switch by determining the share of drivers who made a switch to lower insurance coverage (switchers), and the factors that affected this. In the second model, the impact of making a switch on frequency of claims is investigated.

In order to account for unobserved heterogeneity in both models, we follow Allison (2009) and apply a hybrid method which incorporates features of both fixed and random effects methods.

The first model is estimated by a conditional logit regression method, while a negative binomial regression method is used to estimate the second model. Post-estimation tests suggest that a hybrid method is more relevant than a random effects method in both models.

The results indicate that the share of switchers was 1.76 percent a year prior to the reform, and that this share increased to 2.42 percent a year after, and then continued to increase in the following years. Our findings from the first model suggest that, compared to the pre-reform period, the likelihood of making a switch increased on average by 47 percent after the tax introduction. Interestingly, tax reform had more impact on older drivers by increasing the odds of being a switcher by 98 percent, while the odds for young drivers aged up to 25 were reduced by 15 percent. The results from the second model shows that switching to lower insurance coverage due to the tax reform has no significant effects on the number of claim submissions, which implies that the tax reform had no impact on the driving behavior of switchers. However, a choice of lower coverage in the pre-reform period resulted in a decrease in frequency of claims by 20 percent for drivers aged 35-44, which might be evidence of ex ante moral hazard in vehicle insurance.

The rest of the paper is organized as follows. Section 2 provides the theoretical and methodological framework, where we present the previous literature review, methodology, data description, two models and their estimation procedure. Section 3 contains the empirical results, which combine descriptive statistics and multiple regression outcomes, followed by a discussion of the results of the two models. Section 4 concludes the paper.

2. THEORETICAL AND METHODOLOGICAL FRAMEWORK

2.1 Literature review

Human factors comprising driver performance and behavior are responsible for 95 percent of traffic accidents (Evans, 2004; Petridou and Moustaki, 2001). Driver performance includes knowledge, skill, perceptual and cognitive abilities, whereas driver behavior concerns how to employ these attributes. While it is possible to analyze driver performance by conducting lab experiments and surveys[2], driver behavior cannot be analyzed by the same methodology. Therefore, obtaining quantitative information on driver behavior is challenging.

The impact of vehicle insurance on driver behavior has been analyzed in many studies. Vehicle insurance may negatively affect driver incentives to be careful on the road, because the outcome of driver behavior is insured, i.e. the insurance company bears the costs of driver behavior on the road according to the conditions stated in the contract. This transfer of responsibility from driver to insurance company leads to asymmetric information problems in insurance, which comprises the theories of moral hazard and adverse selection.

The theory of moral hazard states that a driver with vehicle insurance has less incentive to undertake preventive measures on the road to avoid traffic accidents, while the theory of adverse selection suggests that high-risk drivers would be more willing to purchase a high insurance coverage (Richaudeau, 1999).

A core problem of insurance literature on asymmetric information is insufficient empirical research on distinguishing a moral hazard effect from an adverse selection effect.

Different approaches have been used to deepen the understanding of these questions. Weisburd (2010) empirically analyzes the vehicle insurance market in Israel where vehicle insurance is often provided by employers. Moreover, the degree of insurance coverage is determined by the employer regardless of the employee's preferences, which eliminates the adverse selection effects, while the impact of insurance on driving behavior and accidents reflects moral

[2] For instance, Manchester Driver Behavior Questionaire(DBD), Driving Skills Inventory(DSI) etc.

hazard. Weisburd also finds that the possession of employer-provided insurance increases the likelihood of an accident by 3.6 percent compared to drivers who purchase insurance on their own, which then provides evidence of moral hazard. Similarly, Dunham (2003) considers a market for used fleet vehicles (company or rental vehicles) and finds that fleet vehicles depreciate approximately 10 to 13 percent faster than owner-driven vehicles, which might be evidence of moral hazard. This suggests that the separation of ownership and actual operation of a vehicle produces information asymmetries, as the owner of the fleet vehicle cannot directly observe how a driver actually operates a vehicle.

Israel (2004) analyzes experience rating schemes in the US. He allows for general state dependence in claims and finds a moral hazard effect in vehicle insurance. The results also suggest that, given the presence of moral hazard, individuals drive more safely when the costs of claims are high.

Dionne et al. (2004b) also find evidence of moral hazard in the French automobile insurance market. They conclude that experience rating schemes induce high risk drivers to choose lower insurance coverage and improve their unobservable efforts to reduce the probability of having an accident in the next period.

Conversely, Abbring et al. (2003), employing dynamic insurance data, cannot find evidence of moral hazard in the French vehicle insurance market. Likewise, Chiappori and Salanie (2000), using different parametric and nonparametric methods, cannot find evidence of asymmetric information. They conclude that no evidence of asymmetric information can be found if observables are adequately taken into account.

Rate regulation is quite common in the insurance industry, where price setting of insurance policies may be regulated to make it affordable to different categories of drivers. Due to such regulation, the industry may experience incentive distortions, i.e. insurance policies become more affordable to high-risk drivers who, in the absence of rate regulation, may be charged higher premiums in accordance with the risk level. This implies that rate regulation may lead to a crosssubsidization problem where low-risk drivers subsidize high-risk drivers, and may also result in an increased frequency of claims and accidents (Dionne et al., 2012; Tennyson, 2007). Saito (2006) investigates whether rate regulation induces adverse selection or moral hazard in the vehicle insurance market, and finds no evidence of either, while Weiss et al. (2010) find a significant positive association between rate regulation and claim costs and frequency.

Cohen and Dehejia (2004), investigating the effect of vehicle insurance and accident liability laws on traffic fatalities, show that vehicle insurance has moral hazard costs which lead to an increase in traffic fatalities. They also note that increases in the incidence of vehicle insurance[3] and switching to no-fault liability systems[4] have negative effects on traffic fatalities. Heaton and Helland (2010) also confirm that drivers under a no-fault system cause more accidents.

A unifying feature of the incidence of moral hazard and adverse selection is that driver behavior is private information which is difficult for insurance companies to observe. A possible solution to mitigate the problem of moral hazard is to use partial insurance coverage and coinsurance schemes. Partial coverage in the form of a deductible may reduce careless driving incentives by diminishing the risk of loss, so that the moral hazard problem is mollified. Li et al. (2007) analyze the incentive effects of increasing per-claim deductibles and show that a choice of a zero deductible results in higher frequency of claims relative to the choice of non-zero deductibles. If moral hazard leads to an increase in the size of the loss, then coinsurance schemes may alleviate the problem. A deductible is a common instrument against small claims, while coinsurance is more effective against large claims. The experience rating scheme is another widely utilized instrument[5] which provides strong incentives to avoid accidents (Schmidt, 1961; Dionne et al., 2012). Dionne et al. (2004a) show that, under an experience rating scheme, high risk drivers tend to reduce the level of insurance coverage after filing at-fault claims or receiving premium increases, and try to decrease

[3] Discussing the insurance status of vehicles, Blows et al. (2003) argue that uninsured drivers have an estimated four times increased risk of traffic injury compared to insured drivers and they therefore represent a significant public health problem. However, Cohen and Dehejia (2004) find that a reduction in the incidence of uninsured motorists produces an increase in traffic fatalities.

[4] Under a no-fault system, a policyholder is indemnified for personal injuries from his/her own insurance company regardless of fault, and cannot put on trial the other party to compensate for damages and injuries.

[5] In experience rating schemes, claim history is recorded and effectively used in the next contract pricing

the probability of making other claims in the future. Moreover, experience rating schemes increase the efficiency of risk classification by providing additional information to the insurer about the risk level of driver. However, experience rating gives rise to claim underreporting behavior, because filing a claim leads to an increase in premium in the next period.

2.2 Data

The following analysis makes use of individual level data from the largest insurance company in Sweden for the period 2006-2010. The database contains complete information on individual (*IND*) and vehicle (*VEH*) characteristics as well as contract (*CON*) details observed by the insurance company in setting the price of a contract. Individual characteristics cover date of birth, sex, place of residence and no. of household members. Vehicle characteristics include registration number, brand, model, production year and self-reported mileage. Contract details include the premium, duration[6], type[7], claims, damages awarded etc. A complete list of variables is provided in Table A.1 (Appendix A).

The data comprises around 30 percent of all insured passenger vehicles in Sweden; 1.7 million individuals and 2.5 million vehicles over a 6 year period, generating 14.2 million observations.

Income is not explicitly taken into account in the model, instead, a wealth variable is used as a proxy for income. The wealth variable is equal to one if a driver has a vehicle that is up to 3 years old and pays the whole premium without dividing payment into instalments. Therefore, the estimated effect of wealth might represent the effect of income.

[6] Starting and ending period of contract
[7] Full insurance, partial insurance and basic insurance (third-party insurance)

2.3 Methodology

In Sweden, it is mandatory for almost all registered and in-operation[8] motor vehicles to have vehicle insurance if they are used on the road. Generally, there are three types of insurance policies: full, partial and basic (third-party liability). Basic insurance is obligatory and compensates for the personal injuries of the driver and passengers that result from a road traffic accident, regardless of whether the driver is at fault or not. If a policyholder causes an accident, compensation for property damages are paid to the other party, but a policyholder cannot get compensation for own property damages from basic insurance. Partial insurance comprises basic insurance plus fire, glass damage, theft, salvage, engine damage and all-risk cover. Full insurance is a comprehensive insurance which includes partial insurance and vehicle damage cover, and compensates the policyholder for his/her vehicle damages irrespective of whether at fault or not. When a vehicle is not in use and has out-of-operation status, it is possible to purchase "out-of-operation insurance", which compensates for fire, glass damage, theft and other vehicle damages which do not result from collisions.

An exogenous shock in the form of a tax reform may lead to different response scenarios for drivers. Therefore, three groups of drivers are defined. The first group, named "Switcher", consists of drivers who choose a lower insurance coverage compared with their choice of insurance contract in the previous period. For instance, a driver who had full insurance in the previous period now chooses partial or basic or out-of-operation insurance. The second group named "Stable" comprises drivers who do not change their choice of insurance contract compared to the period before. The third group called "Reverse-switcher" is made up of drivers who choose a higher insurance coverage in relation to their choice of insurance policy in the preceding period. For instance, the driver switches from partial (or basic/out-of-operation) insurance, which s(he) had in the previous period, to full insurance in this period. A complete table of possible scenarios is defined, which should facilitate appropriate modeling procedure in the next section (Table 2.3.1).

[8] "In-operation" status implies that a vehicle is in use. If a vehicle is temporarily not in use, e.g. in winter, it is possible to change the status to "out-of-operation", which allows exemption from paying vehicle tax and insurance.

Table 2.3.1 Driver classification based on the choice of a contract

		Period *t*			
		Full insurance	**Partial Insurance**	**Basic insurance**	**Out-of-operation insurance**
Period *t-1*	**Full insurance**	Stable	Switcher	Switcher	Switcher
	Partial insurance	Reverse-switcher	Stable	Switcher	Switcher
	Basic insurance	Reverse-switcher	Reverse-switcher	Stable	Switcher
	Out-of-operation insurance	Reverse-switcher	Reverse-switcher	Reverse-switcher	Stable

The structure of raw data is complex, with unbalanced frequency of appearance of contracts and individuals. An individual may thus have several contracts within a period, which may differ with respect to contract type and duration. Moreover, an individual may have several cars, some of which s(he) insures for one period but not for another. In order to follow the stated methodology, an individual-time panel is constructed using the following sample selection procedure:

- Keep individuals if their contract duration is more than six months. Short-term contracts might be temporarily insured vehicles, for example, driven only on special occasions, so that the drivers do not represent the standard type.
- Keep individuals if they have a maximum of one vehicle. It is possible in Sweden to register a vehicle in the name of a person who is not the actual driver of the insured vehicle, which makes it difficult to identify who is actually driving. Therefore, in order to reduce this bias, individuals with more than one vehicle are excluded from the sample.

Moreover, a time dimension is necessary for constructing the panel. To this end, contracts are separated into several periods conditional on the start date of the contract. After applying the selection procedure described above, our subsample has 3.4 million observations including 1.1 million individuals and 1.2 million vehicles for the 2006-2010 period.

2.4 Modeling

The empirical analysis is conducted with two types of models, a panel data multinomial choice model with unobserved heterogeneity, and a model for count outcomes with unobserved heterogeneity. The first model is applied to identify the share of drivers who made a switch to other insurance coverage compared to the choice of coverage in the previous period, and whether the tax reform, along with the other factors, affected the choice of being a switcher. The second model analyzes whether a switch influenced the frequency of claims. We predict that the tax reform, which led to an increase in insurance premiums, induced some drivers to reduce their insurance coverage by choosing a contract with a lower coverage. Moreover, we also predict that a reduction in coverage led to fewer claims, which may imply a mitigation of ex ante moral hazard. Both predictions are tested in the following two models.

2.4.1 Model I: Propensity for making a switch

In order to estimate the effect of the tax reform, a dummy variable is created which equals 1 if period concerned is the period after July 1, 2007(tax introduction period); 0 otherwise. However, there was a major shift in the economy in 2008, i.e. an economic crisis which may have affected household economic decisions, including the choice of insurance coverage. Therefore, this dummy variable may reflect both a tax effect and an economic downturn effect. To overcome this problem, we assume that individuals responded to the tax reform the year after the tax introduction, i.e. we create a tax effect dummy, *TAXE*, which equals 1 if the period concerned was between July 1, 2007 and June 30, 2008; 0 otherwise. Further, we assume that if an individual did not respond to premium increases the year after the tax introduction, then all responses after this period are attributable to the economic crisis. To capture the economic downturn effects we create a dummy *ECDE* which equals 1 if the period concerned was after July 1, 2008; 0 otherwise[9].

The rationale for these assumptions is that individuals sensitive to premium increases should have responded to the tax reform by reconsidering their coverage choices within a year after the tax introduction, which measures the impact of the tax reform on coverage choice. If individuals remained at their previous coverage but responded in a period when the economic crisis commenced, then this response is ascribed to the economic crisis, so that coverage preference changes after the tax period measures the influence of the economic downturn on coverage choice.

Each driver facing different insurance policies chooses a contract that maximizes his/her utility (U). The utility of driver *n* from alternative *j* in period *t* is expressed through the following equation (Eq. 2.4.1a):

$$U_{njt} = \alpha_0 + \alpha_1 IND_{nt} + \alpha_2 VEH_{nt} + \alpha_3 CON_{njt} + \alpha_4 TAXE_t + \alpha_5 ECDE_t + \mu_{nj} + \varepsilon_{njt} \quad \text{(2.4.1a)}$$

where choice set *j* consists of three alternatives, switcher (*j=1*), stable (*j=2*) and reverse-switcher (*j=3*). Explanatory variables contain three groups: individual-specific *(IND)*, vehicle-specific *(VEH)* and contract-specific *(CON)* variables defined in Table 2.2.1. *TAXE* and *ECDE* are indicator variables for the tax reform and the economic downturn periods, respectively. Unobserved heterogeneity[10] μ captures unobserved individual aspects of driver behavior that are fixed over time but vary between individuals.

Following Train (2003), a logit choice probability that driver *n* chooses alternative *j* in period *t* conditional on explanatory variables *X* and unobserved heterogeneity μ is expressed by equation 2.4.1b:

$$\Pr(y_{nt} = j | X_{nt}, \mu_n) = \int \frac{e^{(X_{nt}\beta_j + \mu_{nj})}}{\sum_{k=1}^{J} e^{(X_{nt}\beta_k + \mu_{nk})}} f(\mu) d\mu \qquad \text{(2.4.1b)}$$

[9] Henceforth, we denote the period between July, 1 2007 and June, 30 2008 a tax period, and the period after July 1, 2008 the economic downturn period.

[10] Henceforth, the terms unobserved heterogeneity and unobserved individual effects are used interchangeably.

2.4.2 Model II: The impact of a switcher on incidence of claims

Let y_{nt} be the claims count for individual *n* in period *t*, which is assumed to have a Poisson distribution with an expected value of λ_{nt}. The probability that $y_{nt} = m$ is given by:

$$\Pr(y_{nt} = m) = \frac{e^{-\lambda_{nt}} \lambda_{nt}^{m}}{m!} \qquad (2.4.2a)$$

where *m* is the number of claims, and λ_{nt} is the conditional mean that depends on several explanatory variables:

$$\lambda_{nt} = E(y_{nt} \mid X_{nt}) = e^{(X_{nt}\beta + SW_{nt}\delta + RSW_{nt}\varphi + TAXE_{t}\gamma + ECDE_{t}\phi + SW_{nt}*TAXE_{t}\psi + RSW_{nt}*TAXE_{t}\vartheta + SW_{nt}*ECDE_{t}\varpi + RSW_{nt}*ECDE_{t}\theta + \mu_{n})} \qquad (2.4.2b)$$

Explanatory variables denoted X_{nt} contain individual-specific, vehicle-specific and contract-specific characteristics specified in Table A.1 (Appendix A). *SW* and *RSW* are indicator variables for switcher and reverse-switcher drivers according to the driver classification[11] defined in Table 2.3.1, *TAXE* and *ECDE* are tax period and economic downturn period dummies, respectively, and following their interactions with switcher effects, μ is an unobserved individual effect.

2.4.3 Model estimation

The presence of unobserved individual effects μ complicates model estimation substantially. Depending on assumptions made for μ, fixed or random effect methods may be applied to obtain parameter estimates. If it is believed that unobserved individual effects have some correlation with observed explanatory variables, then a fixed effect method should be used. Allowing for some correlation between unobserved heterogeneity and explanatory variables creates flexibility in model specification, compared to a random effect method where no correlation between unobserved individual effects and other explanatory variables is assumed.

In the linear panel data case, applying a fixed effects method eliminates μ by taking the first difference of variables in the model and consistently estimates parameters. However, this procedure is inappropriate in discrete choice models (Baltagi, 2008). Besides, if a model contains time-

[11] Stable drivers serve as a reference category.

invariant explanatory variables, applying a fixed effects method eliminates them along with unobserved heterogeneity. Therefore, in order to obtain the coefficient estimates for time-invariant variables, the random effects method should be used.

Another approach to estimating the time-invariant explanatory variables is to use a hybrid method proposed by Allison (2009). A hybrid method incorporates some features of both fixed and random effect methods, where time-varying explanatory variables are decomposed into within-person and between-person parts. The resulting hybrid model contains these two transformed time-varying explanatory variables and time-invariant variables, which are estimated by a random effects method. Coefficient estimates for deviation variables from the hybrid method are functionally equivalent to fixed effects coefficient estimates because these coefficients depend on the variation over time within individuals. Applying this hybrid method provides the possibility of obtaining estimates for time-invariant variables, which would not be possible with a conventional fixed effects method. Therefore, we estimate Model I and Model II by both random effects and hybrid methods.

The choice between random effects and hybrid methods is determined by testing an assumption of the random effects method; i.e., unobserved heterogeneity μ is uncorrelated with the explanatory variables. Implicitly, this assumption implies that the deviation coefficients should be identical to the mean coefficients, i.e. we test the hypothesis of the equality of deviation and mean coefficients. If the hypothesis is rejected, then the hybrid method should be preferred.

A straightforward estimation of a panel data multinomial discrete choice model (Model I) with both hybrid and random effects methods is rather complicated due to the absence of commercial software to perform the model estimation. As a multinomial discrete choice model is a set of several binary models, we split our multinomial model with three choice alternatives into two binary discrete choice models,[12] and use a conditional logit regression method to perform the model estimation. Moreover, an additional analysis (Appendix B) is performed to analyze whether tax

[12] Two binary models: Switcher vs. Stable and Reverse-Switcher vs. Stable, so that Stable drivers is a reference category.

reform caused changes in premiums; we divide our sample into two sub-sample periods, pre-reform (before July 1, 2007) and post-reform (after July 1, 2007) periods. If there are significant changes in price elasticities between pre-reform and post-reform periods, this might be due to the tax reform which caused a structural change in the premium setting. Testing for a structural change is performed with the Zivot-Andrews unit root test, which allows testing for a structural break within panel data (Andrews and Zivot, 1992).

The estimation of the count panel data model (Model II) is performed with Poisson regression where the conditional mean of the outcome is assumed to be equal to the conditional variance. However, this assumption barely holds in practice, where the conditional variance often exceeds the conditional mean and leads to an overdispersion problem. If there is an overdispersion problem, then the coefficient estimates from the Poisson regression are inefficient and standard errors are biased downward. To overcome this problem, a negative binomial regression model is used to allow the variance to exceed the mean. Therefore, the choice between these two regression models depends heavily on the presence of overdispersion effects which are tested by a likelihood-ratio test.

The models described above are fragmented into different age categories in order to reflect heterogeneity in the risk exposure of different age cohorts. For instance, while young drivers may cause accidents due to risky driving behavior, older drivers may cause accidents due to a decline in health state and functional impairment[13].

[13]It is also found that, as young drivers get older, they "mature out" and exhibit less risky driving behavior in the middle-age period, but the risk of traffic accidents increases significantly after age 55. This indicates that the relationship between age and traffic accident involvement is roughly U-shaped (McGwin and Brown, 1999; Begg and Langley, 2001; Jonah, 1986)

3. EMPIRICAL FRAMEWORK

3.1 Descriptive statistics

Table 3.1.1 Descriptive statistics, period from 2006 to 2010

	Obs.	Mean	SD	Min	Max
Age of driver	3442110	53.7337	15.7754	18	105
Age 18-24	53279	0.0154	0.1234	0	1
Age 25-34	374840	0.1088	0.3115	0	1
Age 35-44	666362	0.1935	0.3951	0	1
Age 45-54	690000	0.2004	0.4003	0	1
Age 55-64	748003	0.2173	0.4124	0	1
Age 65 and older	909626	0.2642	0.4409	0	1
No of household members	3442110	1.6876	0.7480	1	10
Male	3442110	0.5812	0.4933	0	1
Residence in metropolitan area	3442110	0.1878	0.3906	0	1
Wealth	3442110	0.0514	0.2208	0	1
Mileage class					
M1: 0-10000 km/year	1672235	0.4858	0.4997	0	1
M2: 10000-15000 km/year	1193538	0.3467	0.4759	0	1
M3: 15000-20000 km/year	392625	0.1140	0.3178	0	1
M4: 20000-25000 km/year	103845	0.0301	0.1710	0	1
M5: 25000+ km/year	79867	0.0232	0.1505	0	1
Vehicle age	3442110	9.9433	6.7822	0	98
Amount of premium	3442110	3450.116	1600.136	100	43936
No of claims	3442110	0.0668	0.3677	0	9

The above table shows that the ages of policyholders range from 18 to 105 and the average driver is 54 years old. It should be mentioned that one cannot be completely certain that the policyholder is the actual driver since people other than the policyholder, such as family members and/or friends, are allowed to drive the policyholder's vehicle. Besides, registering a vehicle in the name of an older person rather than a young person is widely practiced as it is cheaper. Descriptive statistics also show that the share of young policyholders is very small (1.5%) compared to policyholders aged 55 and over (48%). The reason for the small fraction of young drivers represented in the sample is either registration of the vehicle in the name of the parents in order to get lower premiums, or limited financial resources to purchase an own vehicle.

Members of households vary from 1 to 10, with the mean equal to two. The number of male policy holders (58%) exceeds the number of female drivers. Around 19% of drivers live in metropolitan areas where the share of wealthy individuals is about 6.2% compared to 4.9% for those who live outside metropolitan areas. This is in line with the common belief that the income level is higher in metropolitan areas.

As the amount of the premium is positively associated with the declared mileage driven, it is natural to expect that drivers may have an incentive to underreport the driven mileage. In fact, almost 50% of drivers reported the lowest mileage class (up to 10000 km/year), but the more realistic picture could be different, especially taking into account the fact that 81% of drivers live outside the metropolitan areas.

A subsample contains new vehicles as well as very old ones, with the average age of a vehicle being around 10 years. The price of an insurance policy starts from 100 SEK and reaches a maximum of 44000 SEK, whereas the average premium is about 3500 SEK. The distribution of claims also exhibits a high variation ranging from none up to 9 claims, while average claims are around zero, indicating a high frequency of no-claims.

Brief descriptive statistics (Appendix A, Table A.2) for the three groups of drivers, i.e. switcher, stable and reverse-switcher, show that the mean age is highest in the stable driver group

(53), while the lowest is in the reverse-switcher group (50). The shares of drivers aged 65 and more are higher (24 and 26 percent respectively) in the switcher and stable groups, while drivers aged 45-54 are in a majority (22 percent) in the reverse-switcher group. The largest number of males (60 percent), as well as the highest share of metropolitans (22 percent) are in the reverse-switcher group compared to the other two groups. The fraction of wealthy people is highest in the stable group and lowest in the switcher group. Regarding mileage, reverse-switchers (68 percent) drive the lowest mileage per year compared to the other groups, while stable drivers drive the highest mileage per year. On average, switchers drive the oldest vehicles (13 years old), while stable drivers have 9 year old vehicles. The mean premium is highest in the reverse-switcher group, and lowest in the switcher group (4094 and 1595 SEK respectively).

3.2 Multiple regressions

3.2.1 Regression results: Model I

The regression outputs are presented as odds-ratios[14] in the tables below where a multinomial model is decomposed into two binary models, i.e. switcher vs. stable drivers, and reverse-switcher vs. stable drivers.

Table 3.2.1a Hybrid Method: Switcher vs. Stable

	Age 18-24		Age 25-34		Age 35-44		Age 45-54		Age 55-64		Age 65-	
	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE
TAXE	0.841**	0.055	1.024	0.033	1.223***	0.031	1.145***	0.027	1.525***	0.042	1.980***	0.052
ECDE	0.943	0.048	1.129***	0.029	1.371***	0.028	1.367***	0.026	1.736***	0.039	1.735***	0.038
HM	1.006	0.023	0.895***	0.011	0.935***	0.009	0.966**	0.010	0.974	0.015	0.990	0.016
MALE	1.603***	0.075	1.347***	0.032	1.273***	0.023	1.236***	0.010	1.251***	0.024	1.011	0.018
MAR_M	1.430***	0.095	1.537***	0.044	1.872***	0.041	1.862***	0.037	2.063***	0.051	1.867***	0.044
MAR_D	1.013	0.278	2.167***	0.301	2.807***	0.489	3.087***	0.573	4.618***	1.011	3.554***	0.813
W_M	0.242***	0.094	0.159***	0.025	0.084***	0.011	0.124***	0.012	0.087***	0.008	0.069***	0.005
W_D	0.084***	0.053	0.018***	0.004	0.003***	0.001	0.009***	0.001	0.005***	0.001	0.002***	0.000

***, **, * Significant at 1%, 5% and 10%, respectively.

[14] Odds-ratios (OR) are obtained by exponentiation the coefficient estimates from the conditional logit model. OR>1 indicates that the odds of being a switcher increases, while OR<1 implies a decrease in the odds of being a switcher. OR=1 implies that the odds of being a switcher and a stable driver are equally likely to occur.

Table 3.2.1a Hybrid Method: Switcher vs. Stable (cont.)

		Age 18-24		Age 25-34		Age 35-44		Age 45-54		Age 55-64		Age 65-	
		OR	SE	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE
Mileage class													
	M1_M	0.403***	0.101	0.570***	0.057	0.596***	0.044	0.671***	0.044	0.535***	0.037	0.551***	0.073
	M1_D	0.060***	0.034	0.479***	0.105	0.411***	0.070	0.553***	0.089	0.543***	0.091	0.343***	0.093
	M2_M	0.331***	0.083	0.449***	0.045	0.516***	0.038	0.523***	0.034	0.440***	0.030	0.517***	0.069
	M2_D	0.051***	0.029	0.375***	0.081	0.346***	0.058	0.426***	0.067	0.358***	0.059	0.201***	0.054
	M3_M	0.462**	0.124	0.498***	0.054	0.553***	0.044	0.586***	0.041	0.461***	0.034	0.618***	0.086
	M3_D	0.070***	0.043	0.620**	0.140	0.460***	0.081	0.497***	0.081	0.391***	0.067	0.275***	0.075
	M4_M	0.461**	0.170	0.658**	0.090	0.704***	0.071	0.616***	0.056	0.577***	0.054	0.848	0.138
	M4_D	0.154**	0.132	0.598*	0.162	0.671**	0.135	0.671**	0.128	0.576**	0.113	0.575*	0.173
VAGE_M		0.959***	0.002	0.955***	0.002	0.946***	0.001	0.941***	0.001	0.948***	0.001	0.943***	0.001
VAGE_D		0.914***	0.012	0.907***	0.005	0.932***	0.004	0.938***	0.003	0.949***	0.004	0.932***	0.004
PR_M		0.999***	0.000	0.998***	0.000	0.998***	0.000	0.998***	0.000	0.998***	0.000	0.998***	0.000
PR_D		0.999***	0.000	0.998***	0.000	0.998***	0.000	0.998***	0.000	0.997***	0.000	0.997***	0.000

***, **, * Significant at 1%, 5% and 10%, respectively.

Table 3.2.1b Hybrid Method: Reverse-switcher vs. Stable

		Age 18-24		Age 25-34		Age 35-44		Age 45-54		Age 55-64		Age 65-	
		OR	SE	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE
TAXE		0.268***	0.031	0.416***	0.023	0.355***	0.017	0.430***	0.020	0.401***	0.021	0.442***	0.025
ECDE		0.676***	0.060	0.880**	0.039	0.799***	0.032	0.859***	0.034	0.854**	0.040	0.846**	0.045
HM		1.196***	0.048	0.963	0.022	1.042**	0.021	1.155***	0.026	1.263***	0.046	1.664***	0.077
MALE		1.170*	0.101	1.179***	0.051	1.136***	0.044	1.185***	0.044	1.407***	0.065	0.763***	0.038
MAR_M		0.807*	0.094	0.955	0.048	0.940	0.043	0.866**	0.041	0.925	0.054	1.322***	0.084
MAR_D		0.845	0.442	0.329***	0.080	0.194***	0.062	0.727	0.287	0.327**	0.133	0.090***	0.046
W_M		0.560	0.328	0.771	0.161	0.627**	0.102	0.663**	0.104	0.531***	0.083	0.587***	0.089
W_D		1.536	1.420	0.482**	0.140	0.612**	0.125	0.316***	0.061	0.388***	0.071	0.371***	0.058
Mileage class													
	M1_M	2.412**	0.908	3.184***	0.547	4.388***	0.691	1.968***	0.266	1.628***	0.321	6.751***	2.439
	M1_D	3.284	3.024	5.998***	2.299	2.937***	1.049	2.030***	0.738	9.507***	3.978	1.319**	0.857
	M2_M	1.219	0.462	1.402**	0.243	1.511**	0.239	2.479***	0.394	4.069***	0.803	2.208**	0.800
	M2_D	1.584	1.456	1.997*	0.759	1.088***	0.035	1.791***	0.094	2.540***	1.055	5.119***	3.305

***, **, * Significant at 1%, 5% and 10%, respectively.

Table 3.2.1b Hybrid Method: Reverse-switcher vs. Stable (cont.)

		Age 18-24		Age 25-34		Age 35-44		Age 45-54		Age 55-64		Age 65-	
		OR	SE	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE
Mileage class													
	M3_M	0.821	0.335	1.069	0.199	1.200	0.203	1.876***	0.315	2.637***	0.547	1.517	0.572
	M3_D	1.182	1.147	1.399	0.556	1.391***	0.345	3.022**	1.123	1.008***	0.432	1.100***	0.729
	M4_M	0.909	0.472	1.222	0.276	1.019	0.214	0.904	0.198	1.424	0.364	1.419	0.619
	M4_D	0.490	0.575	1.217	0.556	4.123**	1.786	1.174	0.528	7.789***	3.804	1.128**	0.523
VAGE_M		1.059***	0.006	1.076***	0.003	1.068***	0.003	1.071***	0.002	1.074***	0.003	1.068***	0.004
VAGE_D		1.030	0.025	1.057***	0.012	1.066***	0.010	1.072***	0.009	1.027**	0.011	1.040***	0.011
PR_M		1.000***	0.000	1.000***	0.000	1.000***	0.000	1.000***	0.000	1.000***	0.000	1.000***	0.000
PR_D		1.000***	0.000	1.000***	0.000	1.000***	0.000	1.001***	0.000	1.001***	0.000	1.001***	0.000

***, **, * Significant at 1%, 5% and 10%, respectively.

We test the assumption of the random effects method in order to verify whether random effects or hybrid methods are better in explaining the link between explanatory variables and unobserved heterogeneity. The results of a Wald test (Appendix A, Table A.3) suggest that we reject the null hypothesis of equality of deviation and mean coefficients and conclude that the hybrid method (fixed effects method) should be preferred[15].

[15]Therefore, the regression output for the random effects method is suppressed in order to save space.

3.2.2 Regression results: Model II

The regression output is presented as incidence-rate ratios (IRR). The choice between random effects and hybrid methods, as in the previous subsection, is determined by a Wald test, which also shows (Appendix A, Table A.4) a preference for the hybrid method (fixed effects method). A likelihood-ratio test for overdispersion in the hybrid model is performed in order to make a choice between the Poisson regression model and the Negative Binomial regression model; the results (Appendix A, Table A.5) suggest selection of the latter.

Table 3.2.2 Hybrid Method: Negative Binomial Regression Model

	Age 18-24		Age 25-34		Age 35-44		Age 45-54		Age 55-64		Age 65-	
	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE
SW	1.192	0.363	0.799	0.125	0.800*	0.103	0.863	0.115	1.108	0.151	0.806	0.119
RSW	0.709	0.356	1.574**	0.288	1.295	0.225	1.682**	0.293	0.478*	0.180	1.010	0.304
TAXE	1.229***	0.069	1.185***	0.024	1.127***	0.018	1.140***	0.018	1.163***	0.019	1.129***	0.018
ECDE	1.189***	0.063	1.166***	0.022	1.144***	0.017	1.137***	0.017	1.147***	0.018	1.062***	0.016
SW*TAXE	0.991	0.396	0.983	0.212	0.979	0.165	0.838	0.150	0.771	0.138	1.109	0.196
RSW*TAXE	1.183	0.906	0.619	0.211	1.260	0.334	0.853	0.234	3.243**	1.456	1.244	0.519
SW*ECDE	0.659	0.245	1.130	0.203	1.151	0.165	0.922	0.138	0.790	0.121	1.065	0.169
RSW*ECDE	1.068	0.656	0.779	0.186	0.882	0.193	0.804	0.171	2.803**	1.142	1.091	0.377

***, **, * Significant at 1%, 5% and 10%, respectively.

Table 3.2.2 Hybrid Method: Negative Binomial Regression Model (cont.)

	Age 18-24		Age 25-34		Age 35-44		Age 45-54		Age 55-64		Age 65-	
	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE
HM	0.936**	0.021	0.979**	0.008	1.004	0.006	1.032***	0.007	1.009	0.010	0.945***	0.010
MALE	1.033	0.041	0.971*	0.014	0.941***	0.010	0.961***	0.011	0.966**	0.012	1.019	0.012
MAR_M	1.304***	0.067	1.421***	0.024	1.467***	0.018	1.447***	0.018	1.463***	0.020	1.364***	0.018
MAR_D	0.936	0.307	1.328**	0.137	1.328**	0.170	0.947	0.147	1.314*	0.210	1.288	0.220
Mileage class												
M1_M	0.881	0.135	0.884**	0.043	0.879***	0.031	0.861***	0.027	0.705***	0.021	0.716***	0.038
M1_D	1.666	0.887	0.828	0.115	0.944	0.108	0.874	0.102	0.882	0.097	0.873	0.144
M2_M	0.802	0.124	0.873**	0.042	0.898**	0.031	0.883***	0.028	0.780***	0.023	0.817***	0.044
M2_D	1.158	0.614	0.925	0.124	0.995	0.110	0.904	0.101	0.936	0.098	0.922	0.149
M3_M	0.930	0.152	0.911*	0.047	0.917**	0.034	0.894***	0.030	0.855***	0.027	0.880**	0.049
M3_D	1.975	1.098	1.003	0.140	1.035	0.117	0.971	0.110	0.928	0.098	0.888	0.145
M4_M	1.097	0.220	0.874**	0.057	0.923*	0.043	0.977	0.040	0.890**	0.035	1.008	0.066
M4_D	0.946	0.657	0.883	0.144	1.050	0.136	0.974	0.124	0.982	0.114	0.980	0.170
W_M	0.474***	0.101	0.792***	0.039	0.783***	0.026	0.756***	0.024	0.758***	0.021	0.742***	0.019

***, **, * Significant at 1%, 5% and 10%, respectively.

Table 3.2.2 Hybrid Method: Negative Binomial Regression Model (cont.)

	Age 18-24		Age 25-34		Age 35-44		Age 45-54		Age 55-64		Age 65-	
	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE
W_D	0.939	0.483	0.937	0.088	0.901*	0.051	0.753***	0.043	0.883**	0.042	0.887**	0.034
VAGE_M	0.951***	0.003	0.948***	0.002	0.950***	0.001	0.960***	0.001	0.964***	0.001	0.967***	0.001
VAGE_D	0.950**	0.017	0.960***	0.005	0.971***	0.004	0.979***	0.004	0.976***	0.004	0.994	0.004

***, **, * Significant at 1%, 5% and 10%, respectively.

3.2.3 Result discussion: Model I

Our sample consists of around 3 percent switchers and less than 1 percent reverse-switchers, while the rest are stable drivers. The annual switch status pattern (Appendix A, Table A.6) suggests that the share of switchers a year prior to reform, i.e. 1.76 percent, increases to 2.42 percent a year after the reform (2.90 and 3.24 percent in 2009 and 2010, respectively). The share of reverse-switchers rises but marginally so after the reform period. In fact, analyzing reverse-switchers is not of particular interest because choosing a more expensive insurance contract after an increase in premiums does not provide us with meaningful explanation of driver behavior. Despite a low share of drivers who are reverse-switchers, our study presents regression results for this group as well, although the main focus is on the switcher group.

Switchers vs. Stable drivers

The coefficient estimates[16] for the tax reform variable indicate that, compared to the pre-reform and economic downturn periods, the odds of making a switch increase on average by 47 percent for those aged 35 and over after the introduction of the tax reform. Results also suggest that the effect of the tax reform has more impact on older drivers by increasing their odds of being a switcher by 98 percent, and decreasing the odds by 15 percent for drivers aged below 25. This implies that the tax reform increases the likelihood of choosing lower insurance coverage in all age groups except for the youngest drivers. This might be explained by the riskiness of young drivers, who know how risky they are and therefore want to keep their higher insurance coverage in case of an accident, despite the increase in premiums.

The economic downturn increases the odds of being a switcher by 46 percent on average compared to the pre-economic downturn period (i.e. before July 1, 2008) in all age groups except for the youngest drivers. This seems reasonable since the economic crisis directly affects household expenditures where willingness to save may justify switching to lower insurance coverage.

[16] Ceteris paribus is assumed in coefficient interpretation and only statistically significant results are discussed.

The odds of being a switcher for male drivers are on average 34 percent higher than for female drivers. The effect of gender is quite different in various age groups, for instance, the odds of making a switch are 60 percent higher for males than for females aged 18-24, while the odds for males are 25 percent higher compared to females aged 55-64. This implies that, as male drivers get older, the odds of making a switch decrease compared to females.

A family expansion by one member reduces the odds of being a switcher by 10 percent for those aged 25-35 (7 percent for those aged 35-44), while the effect is much smaller for those aged 45-54 (only 3 percent reduction in odds). As the number of family members increases, young drivers seem less likely to choose lower insurance coverage compared to older drivers. This might be due to the higher willingness of young drivers to obtain secure financial stability in case they meet with an accident. Young drivers might be less financially stable and therefore be more sensitive to expenses, especially if supporting a family is part of their daily expenditures.

With the exception of young drivers, living in metropolitan areas multiplies the odds of being a switcher by 2.70 on average compared to drivers living outside metropolitan areas. This implies that drivers living in Stockholm, Gothenburg and Malmo are more likely to make a switch than those living in other cities in Sweden; drivers aged 55-64 have the highest odds of being switchers. This may be explained by higher costs of living in a metropolitan area, where drivers might be more sensitive to changes in prices than those living outside.

On average, the odds of making a switch are reduced by 98 percent for drivers with higher living standards compared to drivers with lower living standards. This implies that the higher the earnings of a driver the less the likelihood of changing to lower insurance coverage. Wealthy drivers aged 35 and over have the lowest propensity to make a switch. This result is quite natural because wealthier drivers are less susceptible to increases in prices compared to less wealthy drivers.

Coefficient estimates for mileage suggest that, on average, the odds of being a switcher decrease by 60 percent for low-mileage drivers compared to high-mileage drivers (more than 10000 km/year). This implies that compared to those individuals who drive more than 10000 km annually, the relative odds of not making a switch increase for those who drive less. This can be explained by the fact that choosing the lowest category of intended driving mileage per year (up to 10000 km) is rewarded with a lower premium compared to the higher categories of intended driving mileage.

As a vehicle gets older, the odds of making a switch reduce on average by 7 percent, and the impact is almost similar across all age groups, implying that drivers are less likely to switch as their vehicle gets older. This might be due to the fact that the premium for an older vehicle is on average lower than for a newer vehicle, which does not make it attractive for the drivers of older vehicles to choose lower insurance coverage.

Each additional increase in premium by one crown is associated with an average 0.003 percent decrease in the odds of being a switcher in all age groups. This small effect of the premium indicates that even if premiums increase, the drivers will be less willing to choose insurance with lower coverage.

Appendix B presents an additional analysis of price elasticities in the pre-reform and post-reform periods. The value of price elasticities at the mean premium, which is close to zero (Appendix B, Table B.1), suggests that an increase in premiums would have very minor effects on the odds of being a switcher in both the pre-reform and post-reform periods. However, the difference in price elasticities between the two periods (Appendix B, Table B.1, column 3) suggests a premium-affecting change in the post-reform period probably due to the tax reform resulting in a structural change in contract pricing. We perform the Zivot-Andrews test to check for possible structural breaks in premium setting for the period from 2006 to 2010. The results (Appendix B, Table B.2) show that around 74 percent of the breakpoints lie within a period from July 1, 2007 to December 31, 2008. This interval may indicate that price changes are both instantaneous and gradual in the post-reform period, i.e. swift shifts in premiums right after reform and some gradual changes in pricing up to the end of 2008. We may also note that these structural changes have asymmetric effects on different age groups; for instance, demand for low insurance coverage decreases for drivers aged 18-24 and 45-54 (Appendix B, Table B.1) and increases for the rest of the drivers. The price elasticity of demand increases by 995 percent for drivers aged 55-64 in the post-reform period, which implies that demand for low insurance coverage rises considerably for this group compared to the pre-reform period. However, despite substantial changes in price elasticities in the post-reform period, the values of elasticities are still small. This indicates that demand for lower insurance coverage is relatively inelastic which implies that exogenous variation in premiums has only a small effect on the choice of lower insurance coverage, and that a premium increase does not lead to strong substitution effects.

Reverse-switchers vs. Stable drivers

A brief discussion of driver behavior in the second group, i.e. reverse-switchers vs. stable drivers, is presented below, though the behavior of this group, i.e. switching to a more expensive insurance after an increase in premiums, is hardly reasonable.

According to the results for household content, each additional household member increases the odds of being a reverse-switcher by 26 percent on average, except for drivers aged 25-34. This implies that in order to decrease vulnerability to possible accident costs, drivers are more likely to choose an expensive insurance when their household increases by one additional person. The effect of the tax reform period suggests that, on average, the introduction of the tax reform reduces the odds of being a reverse-switcher by 61 percent in all age groups. This implies that the tax reform reduces the likelihood of choosing higher insurance coverage compared to the pre-reform and economic downturn periods.

The coefficient estimate for the economic downturn variable suggests that the odds of making a reverse-switch decrease on average by 18 percent during the economic crisis compared to the period before. This result is expected because the purchasing power of individuals drops during economic recessions, which may result in savings on vehicle insurance by choosing less comprehensive insurance coverage.

The odds of being a reverse-switcher increase by 21 percent on average for male drivers compared to female ones, except for drivers aged 65 and above. Male drivers aged 65 and above are less likely to be reverse-switchers than female drivers in the same age group. This implies that, except for older drivers, male drivers are more likely to choose more expensive insurance than female drivers.

On average, residence in a metropolitan area decreases the odds of being a reverse-switcher by 76 percent compared to drivers living outside metropolitan areas, except for the youngest drivers and those aged 45-54. This can be explained by the fact that living in big cities is associated with higher living costs, which makes drivers more price sensitive, so that an increase in prices may lead to a decrease in demand for high cost insurance.

The odds of being a reverse-switcher decrease by 56 percent on average for wealthy drivers, except for the youngest drivers. This implies that wealthy drivers are more likely to remain at their choice of insurance coverage, except for younger drivers for whom the effect is insignificant.

The odds of making a reverse-switch are multiplied by 4.35 for those who drive lower mileages per year compared to those who drive higher mileages, except for young drivers. The effect of mileage driven is quite different across various age groups, but the general picture suggests that drivers who drive shorter distances per year are more likely to be reverse-switchers than those who drive long distances. The reason is that driving less mileage per year leads to a lower insurance premium, which may encourage low-mileage drivers to purchase higher cost insurance compared to drivers who drive longer distances.

As a vehicle gets older, the odds of making a reverse-switch increase by 5 percent on average. It seems that as their vehicles get older, drivers are more likely to switch to higher insurance coverage. This might be due to the fact that older vehicles have lower insurance premiums, which may provide incentives to purchase higher insurance coverage.

The coefficient estimate for the variable premium suggests that the odds of being a reverse-switcher increase by 0.05 percent with each additional one-crown increase in premium. This implies that an increase in premium leads to a very trivial change in the choice of insurance.

Moreover, as in the discussion on switchers above, we estimate price elasticities in the pre-reform and post-reform periods in Appendix B. The value of the price elasticity at the mean premium, which is close to zero (Appendix B, Table B.3), suggests that an increase in premiums has an insignificant impact on the odds of making a reverse-switch; this supports our result for the switcher group. Nevertheless, from Table B.3 (Appendix B) we may note that the significant changes in elasticities in the post-reform period mirror possible structural changes in contract pricing after the tax introduction. Despite large changes in elasticities, an increase in premiums due to the tax reform leads to a very trivial change in the choice of insurance, indicating a relatively inelastic demand for higher insurance coverage.

3.2.4 Result discussion: Model II

Compared to stable drivers, the expected number of claims decreases by 20 percent for switchers aged 35-44 in the pre-reform period, while the effect of switching is insignificant in other age groups. It seems that, in the pre-reform period, switching from higher to lower insurance coverage leads to fewer claims, which might imply that drivers become more motivated to undertake preventive measures due to the increased cost responsibility in case of an accident. This might be evidence of mitigation of the ex ante moral hazard problem.

The expected number of claims increases by 63 percent for reverse-switchers aged 25-34 and 45-54 in the pre-reform period compared to stable drivers, while the claim submission decreases by 53 percent for reverse-switchers aged 55-64 in the same period. This implies that, in the pre-reform period, switching to higher insurance coverage is associated with more claims for middle age drivers, while for older drivers the effect is the opposite, which might be explained by willingness to purchase higher coverage and driving carefully. The behavior of older drivers might be an indication of a propitious/advantageous selection where risk-averse individuals may both obtain comprehensive coverage and drive cautiously (Hemenway, 1992).

The coefficient estimate for the tax period dummy measures the main effect of the tax on stable drivers, which suggests that the number of claims are increased on average by 16 percent for stable drivers. This implies that stable drivers submit more claims compared to switchers and reverse-switchers in the tax reform period.

In the economic downturn period, the expected number of claims is increased by 14 percent for stable drivers. Drivers who remain at their previous coverage seem to have an inclination to submit more claims than those who switch to lower or higher coverage in the pre-reform period.

The interaction between the tax dummy and reverse-switchers suggests that tax introduction multiplies the expected number of claims by 3.77 for reverse-switchers[17] aged 55-64. This implies that, compared to the pre-reform period, making a reverse-switch in the tax reform period increases the number of claims.

The interaction between the economic downturn dummy and reverse-switchers implies that the expected number of claims is multiplied by 3.21 for reverse-switchers aged 55-64 in the economic downturn period compared to the period before the tax reform[18].

Each additional family member on average decreases the frequency of claims by 5 percent for drivers aged up to 35 and those aged 65 and over, while for drivers aged 45-54 the frequency of claims increases by 3 percent. If drivers aged up to 35 have a small child, this may encourage more parental responsibility and lead to more careful driving, which results in fewer claims. The reduced number of claims for the older driver group may be due to a conscious choice of the lowest possible exposure to driving and self-recognition of a declining health state and functional impairment. An increase in claims for drivers aged 45-54 might be explained by additional drivers in the family who share a vehicle with their partners or parents.

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[17] The interaction effect for the tax period and reverse-switchers is computed by: $Exp\left[\ln(TAXE) + \ln(RSW * TAXE)\right]$

[18] The interaction effect for the economic downturn period and reverse-switcher is computed by: $Exp\left[\ln(ECDE) + \ln(RSW * ECDE)\right]$

On average, being a male driver decreases the incidence of claims by 4 percent compared to females, except for the youngest and the oldest drivers. Despite a common belief that males are more risky drivers than females, our results present slightly different evidence which might be explained by the lower willingness of males to report claims.

The frequency of claims increases by 32 percent on average for drivers aged 25-44 and 55-64 living in metropolitan areas compared to drivers of the same ages living outside Stockholm, Gothenburg and Malmo. This can be explained by the high intensity of traffic in big cities which contributes to a higher probability of accidents.

Being a wealthy driver decreases the incidence of claims by 15 percent on average, except for drivers aged 18-34. Wealthy people usually have newer and more expensive vehicles, which encourage them to drive and treat their vehicles with more care. These driver precautions may reduce the probability of making a claim.

As vehicles get older, the expected number of claims decreases on average by 3 percent, except for the older driver group. This might be due to the fact that as a vehicle gets older, a sensation seeking driving behavior is also extenuated, thus exposure to risk which leads to fewer claim submissions.

4. CONCLUSIONS

Driver behavior is considered as a major cause in 95 percent of traffic accidents. Observing and obtaining quantitative information on driver behavior remain complicated despite the development of different methodological approaches in many studies.

Deficiency in observing actual driver behavior generates asymmetric information problems in insurance, because the insurer cannot observe all relevant information about the insured to perform efficient risk classification when setting premiums. Insurance theory predicts a positive correlation between coverage and risk, which reflects two information problems, adverse selection and moral hazard. Adverse selection is when high-risk drivers purchase high insurance coverage, while moral hazard occurs when insuring the financial consequences of careless driving may reduce incentives to avoid traffic accidents. Empirical studies have made efforts to study this correlation between coverage and risk to reveal a possible asymmetric information problem.

In contrast to conventional studies of asymmetric information, this paper analyzes the effect of the tax reform in vehicle insurance through the prism of the literature on asymmetric information, in order to explain changes in contract choice and their effects on the incidence of claims. That is, we construct two models, where the first model analyzes the propensity for making a switch by determining the share of drivers who choose to lower the coverage of the contract (switchers) and the factors that affect the choice of changing to the low-coverage contract. The second model analyzes the effects of changing to a low-coverage contract on the incidence of claims. In order to analyze the effects of the premium increase due to the tax reform on the probability of switching to lower insurance coverage, we use a unique individual level panel data from the largest insurance company in Sweden for the period 2006-2010. The uniqueness of data allows us to model the dynamic relationship between changes in contract choice and claim frequency.

Our results indicate that the tax reform increased the odds of changing to lower insurance coverage by 47 percent on average, with older drivers more affected by the reform than younger drivers. Moreover, the analysis of price elasticities in the pre-reform and post-reform periods shows that the increase in premiums has very minor effects on the likelihood of changing to lower insurance coverage, i.e. demand for lower insurance coverage is relatively inelastic and a premium increase does not lead to strong substitution effects. We also find that switching to low insurance coverage due to the tax reform does not result in any significant changes in claim distributions, though switching in the pre-reform period is associated with a 20 percent decline in the incidence of claims for drivers aged 35-44, which might be an indication of a reduction of ex ante moral hazard in vehicle insurance.

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APPENDICES

Appendix A

Table A.1 Variable descriptions

IND	AGE	Age of driver, years
	MALE	Indicator variable for sex, =1 if driver is male, 0 if female
	HM	No. of household members
	MAR	Indicator variable for place of residence, =1 if driver lives in a metropolitan area (Stockholm, Gothenburg, Malmo), 0 otherwise
	W	Wealth proxy, =1 if driver is wealthy, 0 otherwise
VEH	VAGE	Age of a vehicle, years
	M	Mileage class: M1= 0-10000 km/year M2= 10000-15000 km/year M3= 15000-20000 km/year M4= 20000-25000 km/year M5= 25000+ km/year
CON	PR	Amount of premium, SEK/contract
	CL	Number of claims[19]

[19] In order to make the number of claims comparable across different coverages, we count claims conditional on traffic moment only, i.e. the basic insurance part. More comprehensive coverage allows submitting more claims than the lowest possible coverage, because comprehensive coverage indemnifies a wider range of losses which results in more claims submissions.

Table A.2 Descriptive statistics for three groups of drivers, period from 2006 to 2010

	Switcher (N=90321)		Stable (N=3326825)		Reverse-switcher (N=24964)	
	Mean	SD	Mean	SD	Mean	SD
Age of driver	52.4954	16.2443	53.7911	15.7588	50.6019	15.7634
Age 18-24	0.0328	0.1782	0.0148	0.1208	0.0397	0.1953
Age 25-34	0.1154	0.3195	0.1085	0.3110	0.1364	0.3433
Age 35-44	0.1916	0.3936	0.1936	0.3951	0.1952	0.3964
Age 45-54	0.2148	0.4107	0.1998	0.3998	0.2278	0.4194
Age 55-64	0.2006	0.4004	0.2179	0.4128	0.1961	0.3971
Age 65 and older	0.2447	0.4299	0.2652	0.4415	0.2046	0.4035
No of household members	1.6729	0.7582	1.6878	0.7474	1.7085	0.7812
Male	0.5918	0.4915	0.5807	0.4934	0.6037	0.4891
Residence in metropolitan area	0.2069	0.4051	0.1871	0.3899	0.2241	0.4170
Wealth	0.0058	0.0760	0.0529	0.2238	0.0170	0.1295
Mileage class						
M1: 0-10000 km/year	0.6719	0.4695	0.4792	0.4995	0.6894	0.4627
M2: 10000-15000 km/year	0.2324	0.4224	0.3508	0.4772	0.2226	0.4160
M3: 15000-20000 km/year	0.0646	0.2459	0.1158	0.3199	0.0616	0.2404
M4: 20000-25000 km/year	0.0159	0.1251	0.0306	0.1724	0.0146	0.1201
M5: 25000+ km/year	0.0150	0.1216	0.0235	0.1515	0.0116	0.1073
Vehicle age	13.0723	7.8209	9.8414	6.7202	12.2121	7.7836
Amount of premium	1595.52	1378.01	3495.63	1568.29	4094.12	2294.07
No of claims	0.0594	0.3530	0.0668	0.3678	0.0856	0.4160

Table A.3 Wald test for testing the assumption of random effects method: Model I

	Switcher vs. Stable		Reverse-switcher vs. Stable	
	Chi-square (df)	*p*	*Chi-square (df)*	*p*
Age 18-24	34.94 (8)	0.0000	21.17 (8)	0.0000
Age 25-34	1115.47 (8)	0.0000	167.89 (8)	0.0000
Age 35-44	2846.60 (8)	0.0000	309.19 (8)	0.0000
Age 45-54	2924.40 (8)	0.0000	303.78 (8)	0.0000
Age 55-64	3179.28 (8)	0.0000	475.38 (8)	0.0000
Age 65-	5478.21 (8)	0.0000	486.51 (8)	0.0000

Table A.4 Wald test for testing the assumption of random effects method: Model II

	Chi-square (df)	*p*
Age 18-24	21.38 (7)	0.0000
Age 25-34	24.27 (7)	0.0000
Age 35-44	28.48 (7)	0.0000
Age 45-54	29.64 (7)	0.0000
Age 55-64	18.87 (7)	0.0086
Age 65-	61.43 (7)	0.0000

Table A.5 Likelihood-ratio test for overdispersion in hybrid model

	Chi-square	*p*
Age 18-24	1184.72	0.0000
Age 25-34	10631.11	0.0000
Age 35-44	22244.72	0.0000
Age 45-54	22960.00	0.0000
Age 55-64	23319.80	0.0000
Age 65-	38413.21	0.0000

Table A.6 The annual share of drivers' switching preferences, percent

Switch status	**2006**	**2007**	**2008**	**2009**	**2010**
Stable	97.50	97.88	96.78	96.26	95.88
Switcher	1.76	1.88	2.42	2.90	3.24
Reverse switch	0.74	0.24	0.80	0.84	0.88

Appendix B

Table B.1 Price elasticity of demand in Switcher vs. Stable group

	Pre-reform period	Post-reform period	Change (%)
Age 18-24	5.293e-11	3.143e-11	- 40.62 %
Age 25-34	1.398e-11	5.354e-11	282.97 %
Age 35-44	1.218e-11	8.061e-11	561.82 %
Age 45-54	1.932e-11	2.627e-14	- 99.86 %
Age 55-64	3.781e-12	4.142e-11	995.47 %
Age 65-	6.021e-12	1.829e-11	203.77 %

*Values are in absolute terms

Table B.2 Zivot-Andrews test for structural break

	Full insurance		Partial insurance		Basic insurance		Out-of-operation insurance	
	Break	t-stat	Break	t-stat	Break	t-stat	Break	t-stat
Age 18-24	2007h2	-3.42	2008h1	-3.92	2008h1	-3.41	2006h2	-8.02
Age 25-34	2007h2	-3.66	2008h1	-5.50	2008h1	-4.28	2008h1	-8.21
Age 35-44	2008h2	-3.76	2008h2	-4.87	2008h2	-4.46	2007h1	-7.46
Age 45-54	2007h2	-3.47	2007h2	-3.88	2008h2	-3.13	2007h1	-3.63
Age 55-64	2007h2	-3.68	2009h1	-4.24	2008h2	-3.23	2007h1	-3.29
Age 65-	2008h2	-4.10	2008h2	-4.42	2008h2	-3.27	2007h1	-6.16

Table B.3 Price elasticity of demand in Reverse-switcher vs. Stable group

	Pre-reform period	Post-reform period	Change (%)
Age 18-24	4.621e-11	3.105e-12	-92.23 %
Age 25-34	2.200e-11	2.896e-11	31.64 %
Age 35-44	1.098e-11	7.182e-11	554.10 %
Age 45-54	1.556e-11	9.976e-13	- 93.59 %
Age 55-64	9.804e-12	1.518e-11	54.83 %
Age 65-	6.601e-12	2.130e-11	222.68 %

*Values are in absolute terms