Adverse Selection and Moral Hazard in the Dynamic Model of Auto Insurance

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Preliminary draft: Please do not cite or distribute.

September 25, 2015

Abstract

We use the data on multiple years of contract choices and claims by customers of a major Portuguese car insurance company to investigate a possibility that agent's risk is modifiable through costly (unobserved) effort. Using a model of contract choice and endogenous risk production we demonstrate the economic importance of moral hazard, measure the relative importance of agents' private information on cost of reducing risk and risk aversion, and evaluate the relative effectiveness of dynamic versus static contract features in incentivizing effort and inducing sorting on unobserved risk.

Keywords: dynamic demand, adverse selection, moral hazard, insurance

JEL Classification:

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1 Introduction

Economic literature emphasizes screening through a menu of static contracts with varying degree of coverage as the strategy insurance companies may use to deal with consumer heterogeneity in unobserved risk. However, most car insurance markets incorporate experience rating as an important part of their contracts. This feature ties contract premium to the recent realizations of individual's risk. At the same time the variability in coverage across contracts is limited and is often reduced to the choice between covering third party expenses (liability) or covering all expenses (comprehensive coverage) in the case of at-fault accidents. In this paper we ponder over the reasons for such contract design.

Experience rating allows insurance companies to screen for risk on the basis of the past performance. However, this feature also provides incentives for risk modification. In this case unobserved risk is endogenously determined through individual's effort choice. Previous research did not account for this possibility and therefore it is likely that existing estimates of unobserved factors relevant to the operation of car insurance market are biased. The possibility that risk is modifiable also raises a question as to the design of menu of contracts. Should the insurance company emphasize sorting on risks or incentivizing the risk-reducing effort? And if sorting is important would be better achieved through dynamic incentives tied to the history of accidents (as in experience rating) or through differential exposure to risk (through contracts with different degree of coverage)?

Our analysis is based on a model which assumes that individual's risk could be modified through costly effort. Agents are heterogeneous in their cost of effort and risk aversion. Individual realizations of these factors may in part be unobservable to insurance company and to a researcher. We follow consumers over the multiple time periods (years) as they choose the level of coverage (contract) and the level of effort to stochastically control the risk of accident. Our model incorporates incentives associated with experience rating.

We use data from a major Portuguese insurance company. We have access to a panel of observations on the contract choice as well as claims made by a large number of agents over multiple years. The panel structure of our data allows us to control for intertemporal considerations that affect consumer demand and effort choice if response to incentives is feasible.

Our results indicate that the model with moral hazard and adverse selection performs quite well in rationalizing the data. The estimated parameters are of reasonable magnitude and have expected signs. The implied objects of interest (such as cost of effort or risk premium) also have expected magnitudes. In general, we fit conditional and unconditional shares of offered contracts, unconditional distribution of accidents as well as the distribution of accidents conditional on risk class, contract and individual covariates quite well.

We find evidence of important heterogeneity in individual-level factors underlying risk production and of significant private information related to these factors. The estimation results help to clarify the findings of earlier literature. For example, Chiappori and Salanie (2000) relied on variability in static coverage across contracts to test for the presence of asymmetric information and failed to reject the null of no asymmetric information about individual's risk. Our estimates imply that individual who select into higher coverage in Chiappori and Salanie setting tend to be individuals with low tolerance for risk and low cost of effort and thus are endogenously low risk individuals. The levels of risk chosen by these individuals even under weaker incentives associated with higher coverage are comparable to those chosen by individuals with higher cost and higher tolerance for risk who chose to purchase only liability-related coverage.

Further, an analysis by Cohen and Einav (2007) who revisited this issue by allowing for two-dimensional unobserved type (fixed risk and risk aversion) implies that asymmetric information about idiosyncratic risk is less important than asymmetric information about risk aversion; and that sorting across contracts as well as menu design appears to be largely driven by price discrimination rather than screening for risk. While we find similar magnitudes of variation in risk and risk aversion, an interpretation suggested by our model for this regularity is quite different. If risk is modifiable then variability in risk aversion is endogenously liked to the variability in risk. Therefore any policy attempting to leverage off the risk aversion is bound to impact idiosyncratic risks of affected individuals.

Our estimates further indicates that current system works well in incentivizing risk provision and holding the overall risk in the system quite low. In contrast, experience rating scheme is not very successful in sorting individuals on the risk-related factors and thus does not result in the pricing which is well tailored to idiosyncratic risk. This is possibly a reason for concern since industry inability to price individual risk is likely to soften competition and reduce consumer welfare.

In contrast, we find that the contracts with differential coverage appear quite effective both in sorting on risk-related factors and incentivizing risk provision by exposing consumers to the risk on the margin. We illustrate this point by considering an alternative menu which includes a contract with partial liability coverage. We maintain the experience rated pricing in the full liability coverage and allow for fixed additive discount relative to full liability price for the contract with partial liability coverage. We find that such menu is capable of improving the total welfare as well as resulting in substantial reduction in the total number of accidents. European car insurance industry has been legally prevented from offering contracts with partial liability coverage even though such contracts are used by the industry in some countries (for example Israel). Our analysis, indicates that such legal restraint have real welfare costs.

Our paper contributes to the emerging literature which aims both to measure importance of moral hazard as well as to understand its role in insurance markets. These studies could be divided into two groups. The first group comprises studies related to the health insurance (such as Einav, Finkelstein, Ryan, Schrimpf, and Cullen (2013) as well as Cardon and Hendel (2001)). These studies investigate moral hazard present in the agent's decision about how much health care to consume. These decisions are determined by agent's private type (realized health risk and price sensitivity) and financial incentives provided by insurance contract.

The second group of studies focuses on the auto insurance market (e.g. Chiappori and Salanie (2000), Abbring, Chiappori, and Piquet (2003) as well as Abbring, Chiappori, and Zavadil (2011)). Two last papers are closely related to our research agenda. The first paper formalizes the test for the presence of moral hazard that exploits incentives provided by experience rating. We rely on the same variation in our analysis. The second paper studies importance of ex-post moral hazard in a similar market.

The paper is organized as follows. Section 2 describes the Portuguese insurance market, Section 3 outlines the model and Section 4 discusses the data and documents some descriptive regularities. Section 5 summarizes our estimation methodology. Section 6 reports findings implied by our estimates while Section 7 comments on the results of the counterfactual analysis. Section 8 concludes.

2 Industry Description

Portuguese market for car insurance is similar to other European markets in this industry. In particular, insurance companies usually offer two types of insurance: basic insurance that covers damages to the third party (liability) and comprehensive insurance which include damage to the own vehicle. The liability insurance is mandatory in Portugal.

Pricing of both types of contracts is experience rating based. Under this system each policyholder is placed in one out of 18 experience-rated classes on the basis of their history of claims. Beginning drivers start in class ten. Every year the experience class is updated: if the policyholder did not have any claims in the previous year then his experience class is reduced by one. For every claim that he had in previous year he is moved three classes up. Policyholders in classes below reference class are given a discount over the base premium. Policyholders, in classes higher than reference class pay a surcharge over the base premium. The experience class transitions depend

Table 1: Scaling Coefficient for Various Risk Classes

Risk class	Liability Insurance	Collision Insurance
1	45%	45%
2	45%	45%
3	50%	45%
4	55%	45%
5	60%	60%
6	65%	65%
7	70%	70%
8	80%	80%
9	90%	90%
10	100%	100%
11	110%	110%
12	120%	120%
13	130%	130%
14	150%	150%
15	180%	150%
16	250%	150%
17	325%	150%
18	400%	150%

exclusively on the policyholder's number of claims in previous year and not on drivers' characteristics, vehicle's characteristics, or amount of the claims paid in other years. In addition, only claims in which the policyholder is at least partially at fault, trigger upward transition. Pricing of the basic and collision parts of the insurance contract are based on separate experience classes. While the history of individual's claims is not necessarily public knowledge, a policyholder who switches insurance companies and is not providing his new insurer with his/her claims record gets automatically placed in a class 16 (that is in the class where he would end up if he had 2 accidents in his fist year of driving). Table 1 below summarizes the slope of premium function with respect to the risk class.

Experience rating schemes and the base premium are freely set by the insurance company but are subject to regulatory approval by the supervising authority. In Portugal, insurance contracts are mainly sold via agents. Agents can provide a discretionary discount on the premium that the policyholder is charged.

3 Model

The model rationalizes choices made by an individual while participating in the car insurance market. The individual first enters the market at the time he obtains his driving license, t_1. At this time he becomes affiliated with an insurance company A. We follow individual over time as he repeatedly (annually) returns to this market till the age of $T = 90$, which is the legal limit on the age at which individual can hold driving license.

Driving a car exposes individual to risk of accidents or more specifically to the risk of damage to the health and property for the parties involved in the accidents. An individual is required by law to purchase insurance coverage for the losses associated with third-party damages (liability coverage) in the accidents when he is "at fault," that is he is the one who caused the accident.[1] At the beginning of each period he decides whether to stay with basic liability coverage or to purchase comprehensive coverage that additionally (up to a small deductible) protects him from the risk of damages to his own car. Once the contract is chosen the individual decides on the level of risk, λ_t. Parameter λ_t characterizes the probability of having an "at fault accident."[2] Individual's decisions reflect his risk aversion and his cost of maintaining a given level of idiosyncratic risk summarized

[1] A driver involved in a single-car accident is always considered "at fault."

[2] We focus our attention on "at fault" accidents since losses associated with"not at fault" accidents are covered by the liability insurance of the "at fault" party.

by parameters (γ; θ) respectively.

At the beginning of each period individual may leave company A with a fixed probability ρ. There are a number of reasons for individual to exit a market, such as disease, death or loss of a car. Individuals may also leave company A by switching to a competing insurance company. Anecdotal evidence suggests that individuals usually switch because they have been offered a better price discount by a competitor of A. Since discount cannot be a function of individual's private factors, such attrition does not result in selected sample in the environment without switching costs. In this market insurance companies actively solicit customers (in contrast to the situation where individuals search for a better deal) so absence of (or small) switching costs are not implausible. However, as a robustness check we also investigate the case of endogenous attrition with switching costs. The results are presented in Appendix.

Risk Exposure As we explained above, individual's risk exposure depends on the contract he chooses (y_t), his idiosyncratic risk λ_t, and the distribution of damages to his car in case of an "at fault" accident, F_L. In order to characterize this object we introduce some additional notation.

Let us denote the number of "at fault" accidents in a given period by R_t and the associated vector of monetary damages to own car incurred in these accidents is denoted by $\mathbf{L}_t$ with $L_{r,t}$ denoting damage from accident r.[3] The number of accidents follows Poisson distribution with parameter λ_t chosen by individual. In accordance with previous literature we assume that the distribution of $L_{r,t}$ is independent of λ. We use function $C(y, \lambda; F_L)$ to summarize individual's risk exposure if he chooses contract y and the level of risk λ. Specifically,

$$C(y,\lambda) = \begin{cases} E_{R,\mathbf{L}}[R\bar{C} + \sum_{r=1}^{R} L_r|\lambda] & \text{if } y = y^L \\ E_{R,\mathbf{L}}[R\bar{C} + \sum_{r=1}^{R} \min\{L_r, D\}|\lambda] & \text{if } y = y^C \end{cases}$$

where $\bar{C}$ summarizes accident costs that are not included into damages assessed by insurance company, such as monetarized health deterioration, convenience or psychic costs, D denotes the deductible specified in the comprehensive contract.

Cost of Effort

[3] In estimation, we distinguish between three types of accidents: (a) type 1: damage to own car, no counter party involved; (b) type 2: accidents involves counter party with potential damage to own car; and, (c) type 2: accidents involves counter party without damage to own car. We assume that the type of the accident is exogenously determined and the distribution of losses may depend on the type of the accident.

An individual is able to maintain the level of risk at λ by paying cost $\Gamma(\lambda;\theta)$ such that $\Gamma(\lambda;\theta) \geq 0$ for $0 \leq \lambda \leq 1$, $\Gamma'(\lambda;\theta) \leq 0$ and $\Gamma''(\lambda;\theta) \geq 0$.

Specifically, we assume that

$$\Gamma(\lambda;\theta) = g_0 + \frac{\theta_1}{1+\theta_2\lambda}$$

with $\theta_1 > 0$ and $\theta_2 > 0$. Parameters θ_1 and θ_2 jointly determine the slope and the curvature of cost function (or alternatively the level and the slope of the marginal cost of decreasing risk).[4] These parameters may potentially change over time to allow for the possibility of learning.

Notice that in our specification it is possible to achieve $\lambda = 0$ at potentially high cost. Such situation would arise if individual uses car very rarely (for example, only in emergency), possibly because of steep incentives at high risk classes.[5]

Contract Pricing

Insurance contract pricing is based on experience rating. Individual is assigned to a liability and comprehensive risk for every period that he stays in the market. We summarize individuals risk classification by vector $M_t = (K_t^L, K_t^C)$ such that $M_1 = (10, 10)$. The risk call evolves as a deterministic function of the total number of related accidents (the number of "at fault" accidents with damage to the third party for the liability component and the number of "at fault" accidents with positive damages to own car, $\tilde{R}_t = \sum_r^R 1(L_{r,t} > 0)$ for comprehensive component if individual is enrolled in comprehensive contract).

Contract prices for a given risk class are fixed multiple of the contract price for the risk class 10. An individual therefore anticipates that as his risk class changes so does the price he has to pay for contract y in future periods. We denote price of contract y by $p(y, M)$ to recognize this dependence.

Payoffs

[4]Our model encompasses the case of no moral hazard in the limit; that is, if we set $\Gamma''(\lambda;\theta)$ to be large the model generates minimal risk adjustment in response to the incentives. In practice, even moderate values of $\Gamma''(\lambda;\theta)$ generate negligible and even not numerically detectable risk adjustments, which enables our model to describe the world with no moral hazard during the estimation, if necessary.

[5]In addition, our specification is supplemented with a possibly large parameter $\bar{\lambda}$, which specifies the excessive level of risk over which an individual cannot adjust. The bound reflects the fact that is a certain amount of risk that would be hard to achieve by an individual, who does not engage in perverse driving behavior or suffers from serious health problems.

Individual's preferences are summarized by the within-period utility function

$$U(w+\pi;\gamma) \;=\; (w+\pi) - \gamma(w+\pi)^2,$$

where w denotes individual's wealth and π represents all monetized payoff associated with car insurance market. The payoff in a given period is a function of the contract and risk levels chosen by individual and of his risk classification. Specifically,

$$\pi(y,\lambda,M) = -p(y,M) - C(y,\lambda) - \Gamma(\lambda;\theta).$$

Optimization Problem and Bellman Equation

The state of individuals decision problem is summarized by a vector $s = (\gamma,\theta,M)$; cost and utility parameters are included because they may change over time. An individual decides on a policy function which maps individual's state into a contract choice and risk levels $\mathbf{g}_t(s) = (\boldsymbol{y}_t(s), \boldsymbol{\lambda}_t(s))$ to maximize for all $t \in \{1,...,T\}$

$$V_t(s) = E_{\mathbf{g}}\left\{ \sum_{l=t}^{\min\{\tau-1,T\}} \beta^{l-t}[U(w+\pi(y_l,\lambda_l,M_l))] \middle| s_t = s \right\}, \tag{1}$$

where s_l evolves as described above and τ is the stopping time, reflecting exogenous exit.[6]

The Bellman equation for the above problem is given by

$$V_t(s_t) = (1-\rho)\max_{y_t,\lambda_t} E_{R,\mathbf{L}}\left[U(w+\pi(y_t,\lambda_t,M_t)) + \beta V_{t+1}(s_{t+1}) \middle| y_t,\lambda_t,s_t\right], \tag{2}$$

with a terminal condition $V_T = 0$.

Discussion

These functional forms for the cost of effort and within-period utility function are motivated by specifics of our empirical environment. In our setting risk adjustment could potentially be prompted by two very different sets of incentives. First, individuals respond to incentives imbedded in risk classification and contract pricing. An individual exerts effort to avoid accidents because

[6]The stopping time τ is distributed as a Pascal distribution with parameter ρ, which indicates $\tau-1$ consecutive failures and one success in the series of Bernoulli trials with a success probability ρ.

he anticipates that accident will result in his placement in a higher risk class where he would have to pay higher premium for an insurance contract. Such price incentives are increasing in risk class and the functional forms for cost and utility have to be flexible enough to rationalize responses observed in the data. Second, individual may choose to move from basic liability to comprehensive coverage. In this case his risk exposure will be substantially reduced which prompts him to relax his effort. In our extensive experimentation with functional forms we found that functional forms previously considered in the literature, e.g hyperbolic cost function with an asymptote ($\frac{\theta_{1,i}}{\lambda-\theta_{2,i}}$) with $\theta_{2,i} > 0$ (Abbring, Chiappori, and Zavadil, 2011) and constant risk aversion preferences (same authors), are not capable of generating accident patterns observed in the data. Specifically, they are not capable of explaining high responsiveness of individuals to the relatively small incentives generated by the movement across risk classes under liability contract (which occur for low levels of risk) and very moderate responses invoked by movement across contracts associated with more substantial monetary incentives (that correspond to higher levels of risk). While other modeling devices might have generated similar regularities (we could have allowed for behavioral response to accidents or for external considerations, unrelated to insurance, influencing agents' behavior under comprehensive contract) we find it instructive that the alternative functional forms allow us to reconcile the model and the data to a high degree.

Further, we are concerned that individual's wealth may influence his choices in this setting. Like most of the literature before us we do not have access to the information on individual's wealth. However, we notice that quadratic utility function we use could be re-parametrized in such a way that all information related to individual's risk aversion including his wealth is summarized by a single utility parameter. Specifically, we consider the following re-parametrization

$$U(x; \tilde{\gamma}) = x - \tilde{\gamma}x^2,$$

with $\tilde{\gamma} = \frac{\gamma}{1-2w\gamma}$ where γ is a utility coefficient characterizing original parametrization of the utility function.[7] In fact, since insurance company also lacks information on individual's wealth, coefficient $\tilde{\gamma}$ correctly reflects individual's private information about his risk aversion. That is why, from this point on we summarize individual's private information by a triplet $(\tilde{\gamma}, \theta_1, \theta_2)$.

[7]Notice, that this re-parametrization allows us to preserves an absolute coefficient of risk aversion: under original parametrization we have $RA = \frac{-2\gamma}{1-2\gamma(w+x)} = \frac{1}{(w+x-\frac{1}{2\gamma_i})}$ which is that the same as under the re-parametrized model.

4 Data

Our analysis is based on data provided by a major Portuguese insurance company. For the reasons of confidentiality we cannot name this company; in a subsequent exposition we will refer to it as company A. The sample covers period between 2002 and 2007. This is an unbalanced panel covering 295,000 individuals.

The data contain information on consumer demographics (gender, age, years of driving experience, zip code) and car characteristics (car value, car horse power, car weight, car make and car age). For every driver and for every year in the sample we observe his liability and comprehensive risk classes; whether he chooses basic liability or comprehensive contract; and the premium he pays. We further have access to information on all claims filed by insurees during the sample years. For each claim we observe the date, the size and whether the claim relates to the third-party or own losses.

For the reasons that will be explained later we focus our attention on the subsample of individuals who started their participation in the car insurance market by signing a contract with company A upon obtaining their driving license and have continued their association with this company till and including part of the period covered in the data. Table 2 reports some basic statistics about our sample. As can be seen from the table our sample consists predominately of male drivers; an average driver is 35 years old and has close to 11 years of driving experience. Five percent of drivers in our sample have been driving less than five years. Generally, insurees obtain driving license later in life relative to the US population (average age of first-time drivers is 30 and median age is 33). An average driver owns a car valued at €6,200 euros with the median car valued at €4,000 .

Risk and Associated Expenses. Table 3 summarizes risk associated with "at fault" accidents. As table indicates an average driver has four in hundred chance of an "at fault" accident which results in damage to the third party. Younger drivers face higher risk of 6 in hundred chance of such an accident. Further, the variability of risk in the population of young drivers is higher relative to the general population. The drivers choosing only liability coverage appear to be slightly safer than the general population while young drivers choosing this contract are somewhat riskier than the general population of young drivers.

Table 2: Data Summary Statistics

	Mean	Std. Dev.	5%	25%	50%	75%	95%
Male	0.746						
Age	35.42	4.83	26	29	33	42	45
Age of first-time drivers	29.67	5.04	19	28	33	40	45
Driving experience	10.83	3.54	4	8	10	11	13
Car value, €1,000	6.28	5.98	1.57	2.34	3.91	8.05	18.08
Car weight, 1,000kg	1.27	0.51	0.81	0.94	1.13	1.43	2.52
Car horse power	80.15	25.77	50	60	75	90	130.5
Liability claim (€)	1,784	6,474	238	723	879	1,200	4,313
Comprehensive claim (€)	2,418	3,417	258	652	1,236	2,600	9,142
Comprehensive claim (relative to car value)	0.176	0.257	0.013	0.039	0.084	0.202	0.715
Observations	12,576						

Table 3: Number of Claims

		Liability Claims		Comprehensive Claims	
	Obs	Mean	Std. Dev.	Mean	Std. Dev.
All Drivers	12,576	0.037	0.193		
Young Drivers ($\leq$ 5 years)	629	0.061	0.245		
Liability Contract Only					
All Drivers	11,252	0.036	0.192		
Young Drivers ($\leq$ 5 years)	503	0.062	0.249		
Comprehensive Contract					
All Drivers	1,324	0.043	0.203	0.076	0.282
Young Drivers ($\leq$ 5 years)	126	0.045	0.210	0.121	0.328

The drivers who choose comprehensive coverage are associated with higher number of liability claims. In the context of our model this regularity may arise either due to selection of inherently "riskier" drivers into the contract with higher coverage (adverse selection) or because relaxed incentives associated with higher coverage result into lower effort at risk reduction and thus higher risk (moral hazard). Individuals enrolled in comprehensive contract file claims associated with damage to own car at a higher rate (8 in 100 chance of having a claim or 12 in 100 for young drivers). This is, perhaps, not very surprising since comprehensive claims cover a single car accidents whereas liability claims apply only to multiple car accidents. This regularity may also reflect ex-post moral hazard since the penalty for having an accident resulting in the damage to own car is slightly weaker than the penalty associated with the accident resulting in the third-party damage.

The lower panel of Table 2 provides information on the losses associated with "at fault" accidents. The average liability claim is equal to €1,784 whereas a median claim is €879. The claims could be quite small (€238 (at 5% quantile of the claims distribution) and also quite substantial (€4,313 at the 95% quantile of the claims distribution). While these numbers certainly appear non-trivial recall that an average annual rate of accidents is 0.037. Thus a risk exposure of a risk neutral individual would only be €66 on average (with 5% - 95% inter-quantile range given by €8 to €160). Of course exposure could be six times this amount at the upper end of the risk distribution. Similarly, an average comprehensive claim is €2,418 which is close to 18% of individual's car value (median claim is €1,236 or 8% of individual's car value). Computations similar to those above indicate that the risk exposure of an average driver (if he is risk neutral) would be €104 (with median exposure equal to €53). It appears therefore that the expected risk in the system is not very large while high risk exposure is possible with relatively small probability.

Risk classes, Contracts and Prices. Table 4 summarizes the distribution of data across the risk classes and contracts as well as respective premiums paid by insurees.

In our data majority of observations is associated with lower risk classes (specifically class one) and for every risk class most observations are for the individuals who chose to buy only liability coverage.

Recall that in Portuguese car insurance market the premium is set for the risk class 10 on the basis of individual's demographics and car characteristics. It is then adjusted according to a fixed schedule to account for individual's risk class. The third column of Table 4 reflects the baseline liability portion of the premium (set for class ten) for individuals associated with various risk classes. It indicates that even an average baseline premium is roughly increasing in the risk class. This regularity is primarily driven by the fact that insurance company charges higher premium to younger individuals and individuals with low driving experience who are necessarily located in higher risk classes. The disparity in premiums across classes is quite striking: an individual just entering the system on average has a baseline premium which is twice as high as the baseline premium paid by an individual in class one. Column four shows average of the liability premiums after they are adjusted for the risk class. The difference in adjusted premiums is even more striking with the individuals in high classes paying up to four times more then individuals in risk class one.

Table 4: Statistics Related to Contract Choice

Risk Class	Liability Obs	Liability Base Premium	Liability Adjusted Premium	Comprehensive Obs	Comprehensive Adjusted Premium	Car Value Liability Contract	Car Value Comprehensive Contract
1	8739	536.6	241.5	841	467.2	4939.7	16029.4
2	1369	521.4	234.6	151	477.9	4847.3	16673.3
3	539	481.4	240.7	73	425.8	5153.8	14091.9
4	491	513.7	282.6	62	429.0	4987.4	13384.2
5	234	543.1	325.8	29	655.0	4944.1	14157.6
6	196	583.9	379.5	29	676.7	5211.9	13077.7
7	186	632.5	442.8	31	792.9	5956.4	13087.6
8	206	955.9	764.7	34	1311.1	6117.9	16395.9
9	321	1154.0	1038.6	36	1649.1	5781.0	17127.2
10	253	1169.7	1169.7	26	1755.4	5674.9	15777.3

Column six summarizes comprehensive part of the premium. Comprehensive portion tends to be almost twice as high as the liability portion for the comparable risk class. Thus, individuals purchasing comprehensive coverage on average spend three times as much on car insurance relative to individuals purchasing just the liability portion. Not surprisingly, they tend to be wealthier as indicated by much higher values of cars owned by these individuals (columns seven and eight).

In general, premiums appear to be quite high relative to the average risk exposure for the risk neutral individual. This could be indicative that uncertainty about individual's risk on the part of the industry is quite high which is likely to soften price competition in this market.

Evidence of Moral Hazard. Lastly, we investigate potential presence of moral hazard and the magnitudes of associated effects by regressing the number of claims on individual's characteristics, risk class and the type of contract chosen.The results are summarized in Table 5. According to these results the rate of accidents does not vary in a statistically significant way across risk classes even if we control for years of driving and other individual's characteristics. Similarly, the individuals choosing comprehensive coverage do not appear to differ from those with the liability coverage in a statistically significant way. The results change, however, once we control for individual-specific fixed effects. The results of the regression analysis with fixed effects indicate that individuals drive safer when they find themselves allocated into a higher risk class. Such regularity can only be explained by the presence of moral hazard since sorting across risk classes would work in the opposite direction. Also, consistent with theoretical predictions individuals tend to reduce effort when they have higher insurance coverage. The first effect appears to be larger than the size of the second effect. Years of driving experience are also important determinant of the number of claims. In general, the number of claims declines with the time since obtaining license until about 5 years since license; after that the number of years since license has not effect. This indicates that experience is important in the beginning of the driving career.

Table 5: Evidence of Moral Hazard

	Number of Liability Claims			
Variables	(1)	(2)	(3)	(4)
Constant	0.029 (0.0025)		0.030 (0.0055)	
Risk class	0.004 (0.0008)	-0.066 (0.0022)	0.003 (0.0012)	-0.076 (0.0023)
Comprehensive contract	0.009 (0.0090)	0.041 (0.0279)	0.011 (0.0091)	0.038 (0.0278)
Driving experience – 0 years			-0.002 (0.0237)	0.257 (0.0538)
Driving experience – 1 to 2 years			0.005 (0.0186)	0.226 (0.0503)
Driving experience – 3 to 5 years			-0.004 (0.0194)	0.139 (0.0389)
Driving experience – 6 to 8 years			0.002 (0.0094)	0.017 (0.0063)
Driver FE	No	Yes	No	Yes
N	12,576	12,576	12,576	12,576

5 Estimation Methodology

In this section we discuss identification strategy, parametrization and summarize our estimation approach.

5.1 Identification

We assume that a researcher has access to panel data containing for many individuals their history of risk class placement, contract choices and realized accidents. His objective is to use such data to recover the distribution of individual-level parameters (θ, γ) which summarize the cost of maintaining a given level of risk, and individual preferences for risk.

The main difficulty for identifying these primitives stem from the fact that individual's risk is endogenous and is determined as a response (which differs across private types) to the incentives associated with individual's current risk class and contract choice. Due to sorting, individual's risk class, contract and therefore incentives are endogenous and depend on individual's private information. The challenge is to unravel this dependence. We explain our approach in several steps.

First, consider a one period cross-sectional data on the number of accidents. Aryal, Perrigne, and Quang (2012) establish that the distribution of parameter λ in population can be non-parametrically identified from the data set with this structure and unlimited number of observations. In particular, probabilities of observing various numbers of accidents in the population identify the moments of the distribution of λ. This identification strategy could be applied to a finite dataset (such we have to use in practice) to identify a parametric distribution of λ.

Next, let us consider the case of panel data such that individuals in different periods are allocated into different risk classes (where they are subject to different dynamic incentives) exogenously. Such data would allow us to identify the joint distribution of coefficients determining individuals' risk aversion and the cost of risk under the standard regularity conditions. To see this, abstract away from the correlation between these factors as well as from heterogeneity in risk aversion for now and assume the we observe two separate risk classes in the data.

The observations on the number of accidents under each class provides several moment restrictions for the distribution of λ's chosen under these specific sets of incentives. Since moments of the distribution of λ are functions of the moments of the distributions of the coefficients of the cost of risk function, each of the λ-moments provides an equation that could be used to identify the moments of the distributions of θ_2 and θ_1. Since we have one equation per moment but have twice as many unknown parameters (θ_2 and θ_1 instead of λ) we need to use observations under multiple risk classes in order to identify parameters of interest. The regularity condition necessary for identification is that the moments of λ generate independent equations in moments of (θ_2, θ_1) for different risk classes. This condition generally holds under the optimal contract design.[8]

Since we have access to panel data we can form moments which are based on joint distribution of risk across several risk classes which allows us to recover correlation in individual latent factors.

Finally, let us address identification in the presence of selection into the risk classes. Indeed, in our data the individuals are not assigned into the risk classes as random. Rather they transition into different risk classes on the basis of their realized risk (accidents). To simplify some of the issues related to this selection we focus on the drivers who obtain their license during the period covered by our data and who choose our insurance company upon obtaining the license. According to the contract structure all such drivers start in class 10 and then transition according to the rules of bonus-malus system. Selection introduces obvious problem into the identification strategy described above since the underlying populations in the different risk classes are different. Thus, the equations we describe above do not involve the same set of parameters.

In order to address this issue we propose the following adjustment to our identification strategy. Again, we present our argument in the simplest possible case assuming away the correlation between factors and heterogeneity in risk aversion. We rely on the number of accidents data for our chosen set of drivers for two consecutive periods starting from their first period. By contract design under no circumstances a given driver ends up in the same risk twice during this time. Thus, in every time period this population is subject to different mix of dynamic incentives. This would allow us to form similar set of identifying moment restrictions as well as guarantee that these restrictions are linearly independent locally. As before we can use moments related to the

[8]To illustrate this point consider the parametrization we use in this paper, i.e. $\Gamma(\lambda) = \frac{\theta_{1,i}}{1+\theta_{2,i}\lambda}$. In the absence of the heterogeneity in risk aversion all individuals will choose λ such as $\Gamma(\lambda)$ is constant across individuals. Let's say it is equal to Γ_0. Then, $\lambda_i = \frac{\theta_{1,i}}{\Gamma_0\theta_{2,i}} - \frac{1}{\theta_{2,i}}$, that is, moments of λ_i are linear combination of the moments of $\theta_{2,i}$ and $\frac{\theta_{1,i}}{\theta_{2,i}}$ and the weights of the linear combination depend on Γ_0 which changes with the risk class.

joint distribution of accidents across different time periods. Additionally, any two consecutive periods could be used if we can restrict our attention to the same population of drivers.

We could use the variation in chosen risk across sub-populations exposed to different discount rates to identify the distribution of risk aversion. However, we prefer to follow the strategy previously exploited in the literature and rely on the joint distribution of the contract choices and risk across multiple periods to identify the distribution of the cost of risk and risk aversion in the population.

5.2 Parametrization

We now discuss our econometric model which based on the economic model of insurance coverage and risk level choices outlined in section 3. In this section, we specify how primitives of the model vary across individuals in our setting. We would use this specification to match patterns of risk and coverage choices observed in the data.

An individual in our setting is characterized by a triplet $(\tilde{\gamma}, \theta_1, \theta_2)$. We assume parameters $\tilde{\gamma}$ and θ_2 are fixed whereas parameter θ_1 may evolve over time in a manner consistent with learning. Specifically, we allow that within-individual this parameter may take two values: θ_2^{high} and θ_2^{low}. On obtaining license all individuals start with high level of θ_2 and then stochastically transition to the low level over time; the probability to transition in any give period, p_{low}, is a parameter of the model; low level of θ_2 is an absorbing state. In the interest of tractability we assume the two levels of θ_2 are proportional so that $\theta_2^{high} = \theta_2 \theta_2^{low}$ where θ_2 is a parameter of the model which is constant across individuals.

Next, let x_i denote characteristics of an individual i that are observable in the data. Then, we assume that $(\tilde{\gamma}_i, \theta_{1,i}, \theta_{2,i}^{low})$ are jointly distributed according to the truncated normal distribution (truncated at zero) such that

$$\begin{pmatrix} \tilde{\gamma}_i \\ \theta_{1,i} \\ \theta_{2,i}^{low} \end{pmatrix} \propto TN \left(\begin{pmatrix} x_i \beta_\gamma \\ x_i \beta_{\theta_1} \\ \bar{\theta}_2 \end{pmatrix}, \begin{pmatrix} \sigma_\gamma^2 & \sigma_{\theta_1,\gamma} & \sigma_{\theta_2,\gamma} \\ \sigma_{\theta_1,\gamma} & \sigma_{\theta_1}^2 & \sigma_{\theta_1,\theta_2} \\ \sigma_{\theta_2,\gamma} & \sigma_{\theta_1,\theta_2} & \sigma_{\theta_2}^2 \end{pmatrix}; \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \right).$$

We include in x_i gender of individual, zip code dummy, and dummy corresponding to a car value. We very rarely see individual change location in the data. When this happens we exclude such individual from our dataset (see discussion in the data section). We use individual's average car value in estimation.

We thus estimate mean parameters $(\tau_\gamma, \tau_{\theta_1}, \theta_2)$, variance-covariance parameters $(\sigma^2_\gamma,\ \sigma^2_{\theta_1},\ \sigma^2_{\theta_2}, \sigma_{\gamma,\theta_1},\ \sigma_{\gamma,\theta_2},\ \sigma_{\theta_1,\theta_2})$, and parameters characterizing learning process $(\theta_2,\ p_{low})$. We calibrate parameter $\bar{C}$ to values implied by the studies of the value of life[9] and set it to \$500.[10]

5.3 Implementation Details

TODO

5.4 GMM Estimation

We estimate the model using in two steps. In step one, we recover the empirical distribution of own car damages using claims for consumers that purchased the collision coverage. We condition the claim distribution on car value, and location. We follow the literature in assuming that while individual's risk type is correlated with the number of accidents it is uncorrelated with the size of damages. This regularity permits us uncovering the distribution of damages to own car from the available data. In this step we also estimate the distribution of accident type conditional on the event of an accident.

In the second step we estimate the structural model. We employ a Simulated Method of Moments (see Pakes and Pollard, 1989)[11] with a full solution nested fixed-point approach. We use simulations to integrate over the unobservable individual characteristics $(\tilde{\gamma}, \theta_{1,i}, \theta^{low}_{2,i})$. Specifically, for each individual, we draw a finite number of parameters $(\tilde{\gamma}, \theta_{1,i}, \theta^{low}_{2,i})$. Then, for each draw we solve the dynamic programming problem, and analytically integrate the moments conditional on $(\tilde{\gamma}, \theta_{1,i}, \theta^{low}_{2,i})$ for the optimal paths, starting at $t_i = 1$ (the year individual started to drive). We

[9] CITATIONS

[10] We obtain this number by multiplying the average value of life associated with car accidents, \$500,000 by the probability that an accident results in a fatality or serious injury estimated in these studies to be around 0.001.

[11] Our choice of estimation technique is motivated by the necessity to resort to simulation moments. Since simulated maximum likelihood estimation calls for using a large number of simulation draws we choose to simulated methods of moments in the interest of computational feasibility.

set $K_{i,1}^L = K_{i,1}^C = 10$ and match moments over the observed driving history $t_i \in [\underline{t}_i, \ldots, \bar{t}_i]$. We obtain the unconditional moments by averaging over the draws of $(\tilde{\gamma}, \theta_{1,i}, \theta_{2,i}^{low})$.

During the estimation we incorporate the observed heterogeneity that does not vary over time such as gender, location, average car value, average horse power and average weight of the car, by drawing $(\tilde{\gamma}, \theta_{1,i}, \theta_{2,i}^{low})$ from a conditional distribution. We treat the number of years since driving license as a state variable.

We target the following moments in estimation:

1. The empirical distribution of liability risk classes for a specific number of years after the driving license

$$\mathbf{1}\{K_{i,t}^L = K\}\mathbf{1}\{\text{years driving } \in \mathcal{E}\},$$

for five modal risk classes K depending on experience $\mathcal{E} = [0,2], (2,5], (5,10)$.

2. Number of accidents within risk class and experience level

$$R_{i,t}^L \mathbf{1}\{K_{i,t}^L = K\}\mathbf{1}\{\text{years driving } \in \mathcal{E}\},$$

for five modal risk classes K depending on experience $\mathcal{E} = [0,2], (2,5], (5,10)$.

3. Square of the number of accidents within risk class and experience level

$$\left(R_{i,t}^L\right)^2 \mathbf{1}\{K_{i,t}^L = K\}\mathbf{1}\{\text{years driving } \in \mathcal{E}\},$$

for five modal risk classes K depending on experience $\mathcal{E} = [0,2], (2,5], (5,10)$.

4. Contract choice

$$\mathbf{1}\{Y_{i,t} = Y\}, \quad R_{i,t}^L \mathbf{1}\{Y_{i,t} = Y\}, \quad (R_{i,t}^L)^2 \mathbf{1}\{Y_{i,t} = Y\}, \quad \nu_{i,t}\mathbf{1}\{Y_{i,t} = Y\}, \quad \nu_{i,t}^2 \mathbf{1}\{Y_{i,t} = Y\},$$

for $Y = Y^L, Y^C$.

5. Two-period moments:

$$\mathbf{1}(R_{i,t-1}^L = 0) \times \mathbf{1}(R_{i,t}^L = 0) \times \mathbf{1}(K_{i,t-1}^L = 1).$$

$$(R_{i,t} - R_{i,t-1})\mathbf{1}\{K^L_{i,t_i-1} = 1\},$$

6. Market shares of the comprehensive contract conditional on the price discount

$$\mathbf{1}\{Y_{i,t} = Y\}\mathbf{1}\{D^L_{i,t_i} = D\},$$

for $D = 2.5\%, 7.5\%, ...$

The moments are clustered at the level of an individual insuree.

6 Results of estimation

In this section we summarize findings implied by our estimation results.

First of all we find that the model proposed in the paper is capable of rationalizing available data. Indeed, the estimated parameters of the model reported in Table 6 are of reasonable magnitude, have expected signs and are statistically significant. The estimates reflect regularities documented in other studies such as that women tend to be more risk averse or that the cost of effort is increasing in wealth (as proxied by the car value). The later regularity is consistent with the perception in the literature that the cost of effort is in part the cost of inconvenience (in most cases the cost of inefficiently spent time) which tends to be increasing in individual's income.

We estimate that the cost of effort for inexperienced drivers is substantially higher than the cost of effort for those who had been driving for a while. Our estimates indicate that an inexperienced driver has 40% chance to become experienced in a year. This estimate appears reasonable since not all individuals have an opportunity to drive intensively and thus to learn fast. The estimated rate of learning implies that 92% of drivers become experienced within 5 years. The later is consistent with the regularity documented in the Data section that the driving experience exceeding five years has very little effect on accident rate.

Further, our results indicate that the model fits data quite well. Table 7 compares several measures reflecting consumer contract and effort choices computed from the model to those computed from the data. As can be seen from the table the model fits the contracts' market shares (overall and conditional on covariates) within one percentage points. It is also capable of reproducing the

Table 6: Parameter Estimates

	Estimates	Std.Est
Cost of Effort, Scaling Parameter (θ_1):		
Constant	0.86***	0.008
Medium car value	0.16***	0.004
Large car value	0.45***	0.012
Zip code 1 and 2	-0.30***	0.001
Zip code 3	-0.30***	0.013
Female	0.05***	0.022
Cost of Effort, Reciprocal Parameter (θ_2)	7.20***	0.123
Learning:		
Cost multiplier	2.53***	0.021
Probability of learning	0.40***	0.025
Risk Aversion, (γ):		
Constant	7.51***	0.008
Car value (linear term)	1.90***	0.028
Zip code 1 and 2	-0.60***	0.046
Zip code 3	0.25***	0.088
Female	0.20***	0.006
Higher Order Parameters:		
$\sigma^2_{\theta_1}$	0.03***	0.007
$\sigma^2_{\theta_2}$	4.00***	0.038
σ^2_{γ}	1.89***	0.045
$\sigma_{\theta_1,\theta_2}$	0.00	0.007
$\sigma_{\theta_1,\gamma}$	-0.14***	0.012
$\sigma_{\theta_2,\gamma}$	1.79***	0.072

The three stars in parenthesis, ***, indicate significance at 95% significance level. The omitted category are the individuals with low car value who live in the locations with zip codes belonging to group four.

average accident rate conditional on the contract, conditional on the car value (that is, within the groups with different risk aversion), and across risk classes.

We are somewhat less successful in fitting the variance of the number of accidents conditional on comprehensive contract. This is most likely explained by the fact that we do not observe that many individuals selecting this contract especially for some values of covariates (such as low car value). Further, it appears that a very flexible functional for the cost of effort and utility function is required in order to reconcile risk adjustment response to incentives both across contracts and within the contract across risk classes. While our functional forms are quite flexible (we allow for the first and the second derivative to vary) it is possibly not flexible enough to completely capture variability in accidents across individuals and in response to various incentives.

Figure 1: Distribution Over Risk Classes

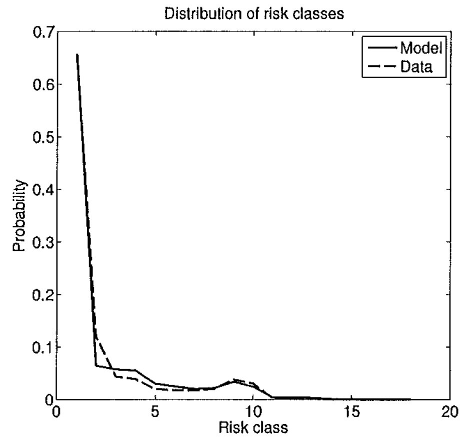


Table 7: Fit to the Data

	Model	Data
Market Share of Comprehensive Contract		
overall	0.107	0.113
conditional on		
low car value	0.010	0.008
medium car value	0.055	0.052
high car value	0.366	0.396
low discount	0.095	0.086
medium discount	0.129	0.119
high discount	0.128	0.138
Average Number of Liability Claims Conditional on		
liability contract	0.039	0.040
comprehensive contract	0.049	0.044
low car value	0.042	0.042
medium car value	0.041	0.044
high car value	0.036	0.036
0-3 years experience	0.077	0.079
3-5 years experience	0.048	0.047
liability risk class 1	0.037	0.036
liability risk class 2-4	0.041	0.044
liability risk class 5+	0.040	0.040
Std. Dev. Number of Liability Claims Conditional on		
liability contract	0.199	0.203
comprehensive contract	0.221	0.206

The dynamic fit of our model is summarized in figure 1 which plots the distribution of individuals across liability risk classes in the data together with the distribution of these individuals across classes simulated from the model. The two graphs are quite close which indicates that the model captures the dynamic evolution of individuals' histories in population quite well.

Importance of Asymmetric Information We find that all individual-level parameters, $(\theta_1, \theta_2, \gamma)$, exhibit non-trivial variation both in their observable and unobservable components (see Table 8). We find significant positive correlation between the cost function parameters, θ_1 and θ_2, and the utility parameter capturing individual risk aversion, γ, in the unconditional distribution of these factors. In contrast, unobservable parts of θ_1 and γ appear to be negatively correlated. Positive correlation between θ_2 and γ appears to be stronger for unobservable components relative to the correlation observed in unconditional distribution. In both cases it appears that the correlation in observable components of these factors has an opposite sign of the correlation in the unobserved parts.

Table 8: Estimated Distribution of Individual-level Parameters

	Mean	Std. Dev.	25%	50%	75%	$\rho(\cdot,\theta_1)$	$\rho(\cdot,\theta_2)$	$\rho(\cdot,\gamma)$
Unconditional Distribution								
θ_1	0.80	0.30	0.57	0.77	1.00	1.00	-0.00	0.09
	(0.010)	(0.007)	(0.010)	(0.011)	(0.014)	(-)	(0.005)	(0.021)
θ_2	7.21	2.01	5.85	7.20	8.58	-0.00	1.00	0.51
	(0.121)	(0.095)	(0.154)	(0.121)	(0.120)	(0.005)	(-)	(0.009)
γ	8.06	1.47	7.04	8.16	9.36	0.09	0.51	1.00
	(0.028)	(0.017)	(0.038)	(0.035)	(0.040)	(0.021)	(0.009)	(-)
Purged of Observable Variation								
θ_1	0.00	0.18	-0.12	-0.00	0.12	1.00	-0.01	-0.54
	(-)	(0.003)	(0.002)	(0.000)	(0.002)	(-)	(0.001)	(0.012)
θ_2	0.00	2.01	-1.37	-0.01	1.37	-0.01	1.00	0.62
	(-)	(0.095)	(0.067)	(0.006)	(0.067)	(0.001)	(-)	(0.010)
γ	0.00	1.22	-0.80	0.13	0.75	-0.54	0.62	1.00
	(-)	(0.014)	(0.012)	(0.010)	(0.014)	(0.012)	(0.010)	(-)

Table 9 reports some implied measures which quantify importance of the observed and unobserved individual heterogeneity in relation to risk production and the cost of risk. Specifically, we compute a measure that for each individual reflects marginal cost of changing individual-specific rate of accidents from population average (0.08) by one percentage point. The distribution of this measure is thus informative of the variability of the cost of effort in population. Additionally, for each individual we compute a risk premium this individual would be willing to pay to avoid all the risk to his car associated with an average rate of accidents (0.08). This variable provides a monetarized measure of risk aversion; and the distribution of this variable informs us about the variability of risk aversion in population. In the future exposition we refer to the measures described above as 'marginal cost' and 'risk premium' in the interest of briefness. Table 9 summarizes the distributions of these measures in population. It also reports the distribution of risk induced by agents' equilibrium choices.

The results show that the cost of reducing the risk by one percentage point on average is equal to €24 with the standard deviation of €13. Drivers in this population are quite risk averse since they are willing to pay risk premium of €154 to avoid risk exposure of €100 (recall this number from the Data section). The risk premium has a standard deviation of €295 in the population indicating that important fraction of drivers are very risk averse. We find that important heterogeneity in costs and risk aversion is present in this environment although individuals are more heterogeneous with respect to their risk aversion. The unobserved component of both factors captures close to 75% of variation. The table also documents important variability of the private component of idiosyncratic risk: the risk within 25%-75% quantile range almost doubles. Thus, asymmetric information plays important role in this setting.

The previous literature commented on the relative importance of private variability in individual's risk aversion as opposed to the private variation in idiosyncratic risk. For example, Cohen and Einav (2007) find that in Israel market for liability insurance variability in risk aversion is 2.5 as important as variability in idiosyncratic risk. We document similar difference in the variability of risk and risk aversion. However, in the context of Cohen and Einav (2007) this regularity implied that private information about idiosyncratic risk may play secondary role in the pricing and contract design decisions. Instead, insurance company maybe placing more weight on price discrimination relative to screening on risk. In the context of our model, the idiosyncratic risk is endogenous and is determined in part by individual's risk aversion. Therefore, any pricing or contract feature which exploits individual's risk aversion is likely to affect risk production. Thus, comparison of relative importance of risk and risk aversion is meaningless in the context of our model.

Further, negative correlation in the costs and risk aversion parameters as well as possibility of risk adjustment sheds light on another seminal result. Chiappori and Salanie (2000) found little evidence of sorting on risk across the contracts with differential coverage. Our results indicate that the individuals who are most likely to choose greater coverage tend to be very risk averse. Due to the negative correlation in cost and risk aversion such individuals also tent to have low marginal costs. Thus, in equilibrium such individuals are likely to be endogenously low risk even in the presence of weaker incentives associated with greater coverage. Their risk is quite likely to be comparable to the risk chosen by individuals with higher costs and greater tolerance for risk who however choose the contract with stronger incentives.

Table 9: Some Implied Measures

	Unconditional Statistics			Unobserved Components	
	Mean	Standard Deviation	Coefficient of Variation	Standard Deviation	Coefficient of Variation
Accident rate	0.080	0.038	0.475	0.035	0.443
Marginal cost	24.832	13.401	0.540	10.809	0.435
Risk premium	153.561	294.589	1.918	215.182	1.401

Cost vs. Risk Aversion in Risk Provision. Table 10 investigates relative importance of the cost of effort and risk aversion in risk production. The table reports statistics characterizing the distribution of risks in the population under three scenarios: (a) baseline model; (b) an environment where all individuals have cost parameters set to the mean of the unconditional distribution while preserving individuals' heterogeneity in risk aversion; (c) an environment where all individual have their risk aversion coefficient set to the mean of unconditional distribution while the heterogeneity in costs is preserved. The results reported in the table indicate that variability of risk is importantly reduced when variability of one of the factors is shut down. Although, the risk appears to be more responsive to the heterogeneity in cost parameters. Notice that the variability in risk could not be decomposed into the sum of the variabilities in cost and risk aversion. This is because these two factors are strongly correlated in population.

Table 10: Risk Decomposition

Years Driving	Avg. λ	Baseline		Homogenous marginal cost		Homogenous risk aversion	
		Standard Deviation	Coefficient of Variation	Standard Deviation	Coefficient of Variation	Standard Deviation	Coefficient of Variation
1	0.123	0.042	0.340	0.011	0.091 (-73%)	0.017	0.136 (-60%)
3	0.087	0.034	0.386	0.012	0.138 (-64%)	0.012	0.134 (-65%)
5	0.073	0.031	0.426	0.012	0.171 (-60%)	0.011	0.144 (-66%)
10	0.069	0.030	0.433	0.003	0.039 (-91%)	0.009	0.124 (-71%)
20	0.069	0.030	0.434	0.002	0.034 (-92%)	0.008	0.119 (-73%)
40	0.069	0.030	0.434	0.002	0.034 (-92%)	0.008	0.118 (-73%)

Impact of Risk Provision Incentives Dynamic considerations generated by the slope of the pricing schedule across risk classes are likely to induce risk adjustment by drivers. Figure 2 displays the levels of risk optimally chosen by individuals with low car values when they are associated with the risk class at random (exogenously) rather than on the basis of their driving history. We also disregard learning and evaluate individual's behavior on the basis of their low (long-run) marginal cost of effort. The figure shows that levels of risk chosen by individuals decline importantly with the risk class. The reduction in risk is extreme in classes above class 10. In this region the incentives are so strong they they reduce an expected level of risk to 0.5%. The chosen levels of risk increase after risk class 15. This is because the price incentives disappear at this point since individual is always guaranteed the placement in class 16 by the law.

Figure 2: Long Run Risk Provision

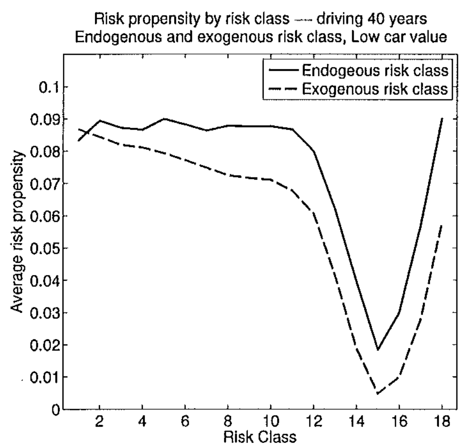


Table 11 quantifies these responses. It indicates that on average individuals are quite responsive to the incentives. Specifically, on average an individual in this market reduces his risk 9% when he is moved from class one to class five, and by 18% when he is moved from class one to class ten. As we indicated earlier the incentives really kick in after class ten so that the accident rate chosen in class 1 is reduced by half once the individual is placed into the class 13. The results in the table also indicate that individuals are quite heterogeneous in their responses. The risk rates chosen by individuals in 25% and 75% of the risk distribution differ by five percentage points. Heterogeneity in responses is lower in higher risk classes where incentives are stronger.

As we would expect exogenous moving from liability contract to comprehensive contract would also induce risk adjustment by drivers which is traditionally called "moral hazard" in the literature. This response is comparable in magnitude to that observed in the lower risk classes. That is, while

Table 11: Long Run Risk Provision by Class

Risk Class	Exogenous: Average Accident Rate	Exogenous: Relative to Class One	Endogenous: Average Accident Rate	Endogenous: Relative to Class One
1	0.087	–	0.083	–
2	0.084	-0.034	0.089	0.072
3	0.082	-0.057	0.087	0.048
4	0.081	-0.069	0.087	0.048
5	0.079	-0.092	0.09	0.084
6	0.077	-0.115	0.088	0.060
7	0.075	-0.138	0.086	0.036
8	0.072	-0.172	0.088	0.060
9	0.072	-0.172	0.088	0.060
10	0.071	-0.184	0.088	0.060
11	0.068	-0.218	0.087	0.048
12	0.06	-0.310	0.08	-0.036
13	0.041	-0.529	0.062	-0.253
14	0.019	-0.782	0.039	-0.530
15	0.005	-0.943	0.018	-0.783
16	0.01	-0.885	0.03	-0.639
17	0.028	-0.678	0.057	-0.313
18	0.058	-0.333	0.09	0.084

not drastic it is also non-negligible.

Having documented the magnitudes of risk responses that arise under exogenous allocation we turn to the analysis of the risk levels that arise under real-life operation of this system which in addition to risk provision also facilitates sorting of individuals across risk classes. The impact and importance of sorting could be already seen in figure 2 by comparing the levels of risk chosen under exogenous and endogenous allocation. The later is based on the long-run (hypothetical) positions of individuals who progressed though the risk classes according to the rules of experience rating. As can be easily seen in the figure the average risk profile under endogenous allocation is much flatter and is actually upward sloping for some of the lower risk classes. Only in the classes above ten the risk profile is downward sloping. It closely tracks average risk under exogenous allocation while remaining always above by two percentage points on average.

The discrepancy in the levels of risk under exogenous and endogenous allocation is indicative of sorting. Indeed, the individuals for whom low levels of risk are economically justified progress downward across risk classes and are more likely to find themselves in a lower rather than higher risk class. Individuals who remain in higher classes either have higher cost of adjustment or higher tolerance for risk, and are thus endogenously high risk drivers. Specifically, their chosen levels of risk substantially exceed the average levels of risk that would have been chosen in those classes by non-selected population. Interestingly, the worst drivers would be stuck in classes above class ten. However, experience pricing punishes them with extreme incentives so that in equilibrium their risk is substantially below the risk of more flexible individuals.

This analysis indicates that sorting has important implications for risk production. We investigate the magnitudes of sorting induced by experience rating next.

Implications for Sorting Experience rating system facilitates sorting of individuals into risk classes on the basis of their history of accidents. We first investigate the sorting that could be achieved in the long run and then turn our focus to a short-run sorting. Our analysis indicates that in the long-run 99% of individuals end up in classes 1-8 with 70% located in class 1. This either suggests that sorting is not very effective or that the individuals are homogenous relative to the filters employed by the experience rating.

In figure 3 below we plot the distribution of marginal costs and risk premiums defined as above for the individuals who endogenously end up in classes one, ten and sixteen in the long run. We show these graphs for the individuals with low and high car values separately. Let us first consider individuals with low car value. The figure indicates that sorting is indeed present. That is in the long run the individuals who end up in class one are characterized by lower marginal cost of adjusting risk and higher risk aversion relative to the individuals who end up in class 10 or 16. In the case of marginal costs this difference is mostly manifested by the difference in means, whereas in the case of risk aversion the distributions differ by the mass they allocate to the upper tail (that is, by the probability of individual to be very risk averse). Nevertheless, the supports of these distributions remain largely overlapping across classes. Since classes one and 16 are drastically different in their past risk characterization it appears that experience rating is not very effective in sorting individuals on their risk attributes. This is mostly because accidents are quite rare and some individuals that are endogenously quite risky manage to reach lower classes undetected.

Further confirmation of this regularity can be found in the Table 12. To generate this table we have chosen an individual who is average of the basis of his observables (he is a men of 30 years

Figure 3: Sorting across Risk Classes

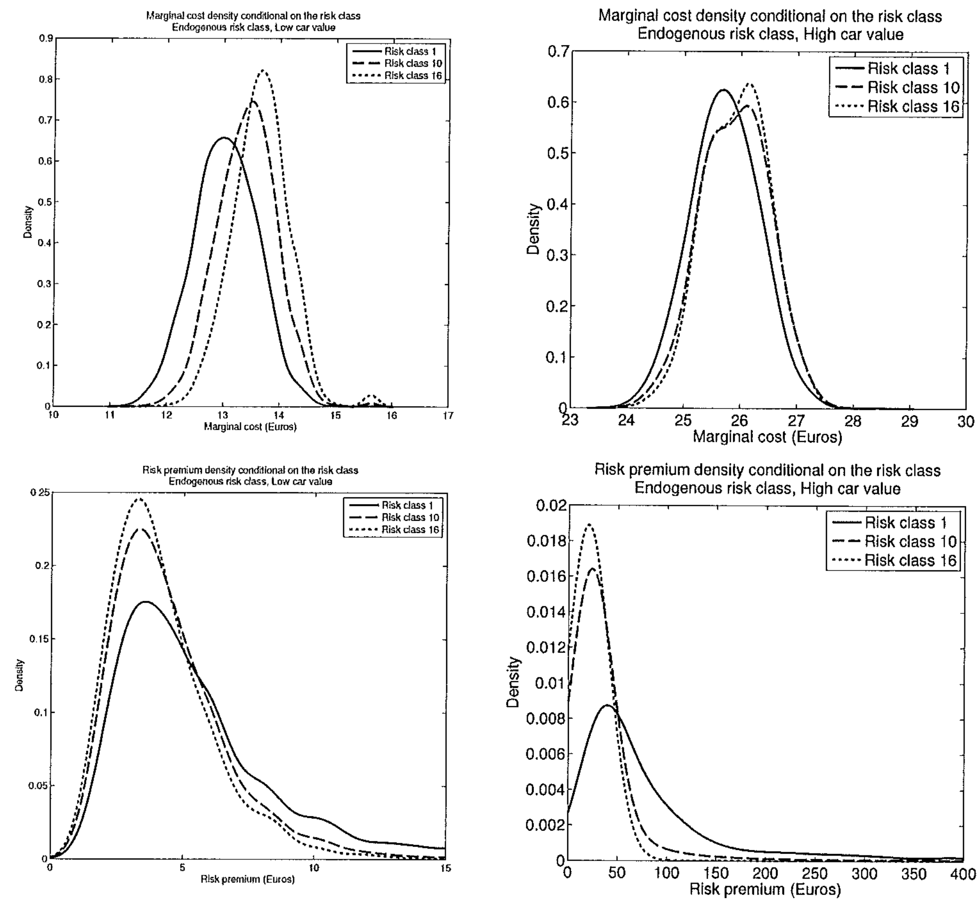
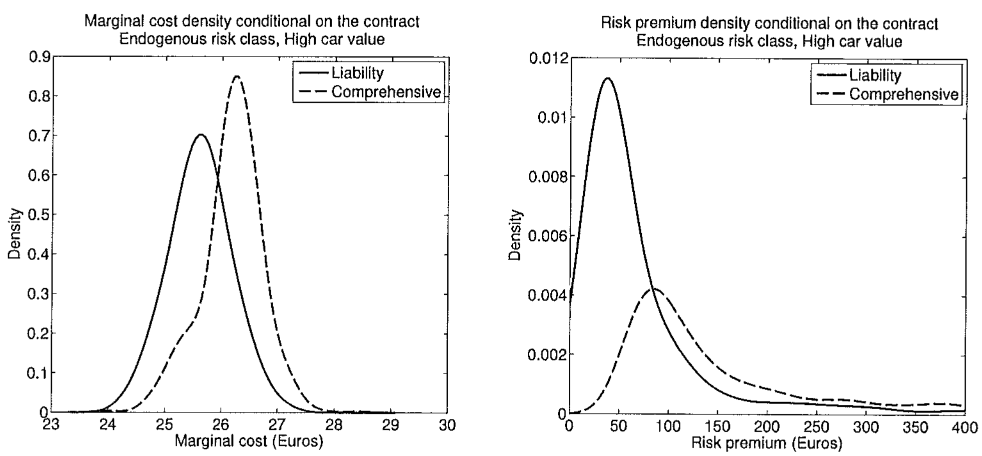
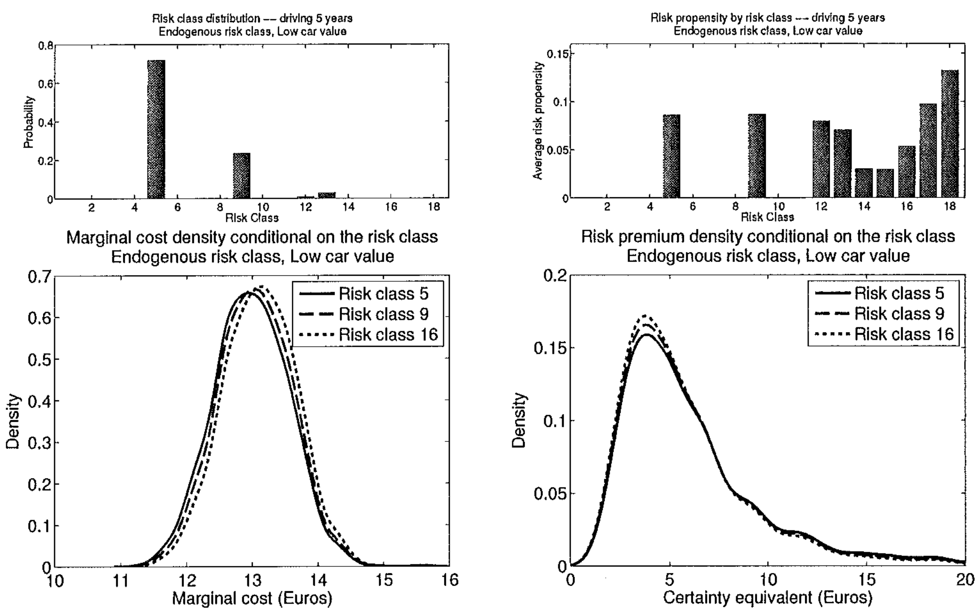


Figure 4: Sorting across Contracts



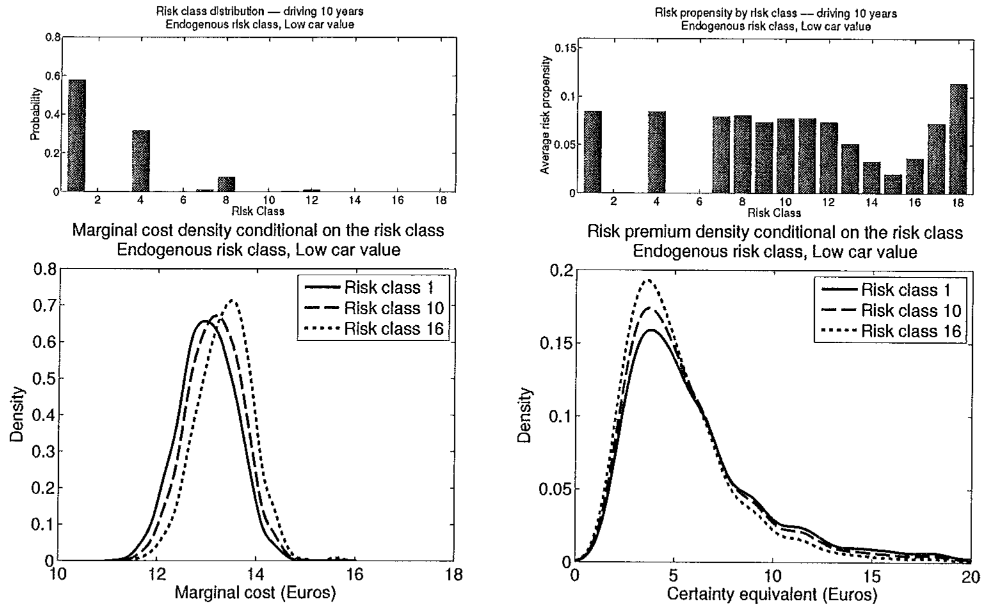
old who lives in zip-code of type 1 and owns a low value car). For this individual we generated an artificial sample consisting of individuals who are his identical replicas in terms of observables but have different realizations of unobserved factors. We then documented the risk class assignment of each of these individuals over the course of 40 years after obtaining a driving license. Table 12 reports an explanatory power of the regression (R^2) relating individual's marginal cost of effort and the risk premium he is willing to pay to achieve full insurance to the liability risk class he finds himself in after a certain number of years. As can be seen from this table the placement in a given risk class provides very little information about individual's unobserved cost or risk aversion.

Figure 5: Short-Term Sorting: 5 years



Let us now consider individuals with high car values. A sizable fraction of these individuals enroll in the contracts with comprehensive coverage once they reach lower risk classes (the comprehensive contract is too expensive for most individuals when they are in high risk classes). The right panel of figure 3 indicates that sorting on the marginal cost is even less pronounced then in the case of the low car values. The distribution of marginal costs appears to be almost identical across classes. The sorting on risk aversion across risk classes appears to be more important. Figure 4 documents sorting across contracts which appears to be more significant. Turning again to the Table 12 we can sees that in the long run the contract choice has significantly higher predictive power than the risk class allocation. This regularity holds both for the marginal cost and for the risk aversion. Interestingly, risk class placement is slightly more informative about individual's marginal cost whereas contract choice is significantly more informative about individuals risk aversion. In any case sorting across contracts appears to be more pronounced relative to the

Figure 6: Short-Term Sorting: 10 years



sorting into risk classes. Thus, differential coverage is more effective in sorting individuals on their unobserved factors.

We also investigate sorting in the short run, that is after individuals have been driving for one, three, five or ten years. Figures 5 and 6 and Table 12 illustrate the information acquisition through experience rating. As can be seen by comparing figure 5 and 6 more information is revealed with time. However, even after five years very little sorting across classes has occurred. This is confirmed in Table 12. Not surprising the sorting on risk classes provides no information in the early years both for the drivers with low and high car value. After 5-10 years of driving the risk class does contain some information about the type but this information is extremely limited. As before, selection into comprehensive contract (which becomes economically viable after 5 years) is much more informative about the agent's type than his placement into the risk class.

7 Illustrative Exploration of Contract Design

Our findings about moral hazard and private variation in the related factors have implications for contract design. Specifically, an insurance company may emphasize dynamic pricing based on experience rating whereby incentivising risk provision or it may focus on offering a more extensive

Table 12: Measuring Sorting

Driving Years	Included Variables	Marginal Cost	Risk Premium
Low Car value			
1 year	Risk class (RK)	0.000	0.000
3 years	Risk class (RK)	0.000	0.001
5 years	Risk class (RK)	0.002	0.003
10 years	Risk class (RK)	0.008	0.012
40 years	Risk class (RK)	0.008	0.009
High Car value			
1 year	Risk class (RK)	0.000	0.005
	RK + Compr. contract	0.003	0.800
3 years	Risk class (RK)	0.000	0.010
	RK + Compr. contract	0.006	0.419
5 years	Risk class (RK)	0.000	0.015
	RK + Compr. contract	0.003	0.537
10 years	Risk class (RK)	0.001	0.027
	RK + Compr. contract	0.138	0.332
40 years	Risk class (RK)	0.011	0.009
	RK + Compr. contract	0.166	0.319

menu of static contracts aimed at screening customers and thus pricing their risk differences in. In the presence of moral hazard risk provision incentives could be implemented in the context of static contracts by introducing partial coverage for liability claims which exposes customers to more risk on the margin.

Historically, European companies have been legally prevented from offering such contracts due to the prevailing law on minimal coverage. As a result European insurance practitioners place larger emphasis on the dynamic risk provision incentives delivered through experience-based pricing. In this section we investigate implications of offering an additional contract with reduced coverage. We implement the following counterfactual exercise. We add a new contract which offers a liability coverage with a deductible tied to individual's car value. The price of such contract is set to be equal to the price of liability contract with additive discount which is constant across risk classes.

Implications for Drivers' Choices

We begin by investigating individual's decisions when faced with such alternative menu of contracts. Figure 7 illustrates selection as well as implications for consumer choices. To isolate these issues from those related to endogenous sorting into classes we construct these graph by exogenously associating individuals with risk classes. We maintain, however, that individuals expect their risk classes to be adjusted according to the rules of experience rating in the future. Individuals are allowed to reconsider their choice of contract each period. As a result we have a non-selected population associated with each risk class and all individuals in the same class face the same implications of an accident on future prices regardless of the contract they choose.

Figure 7: Implications of Partial Liability Coverage

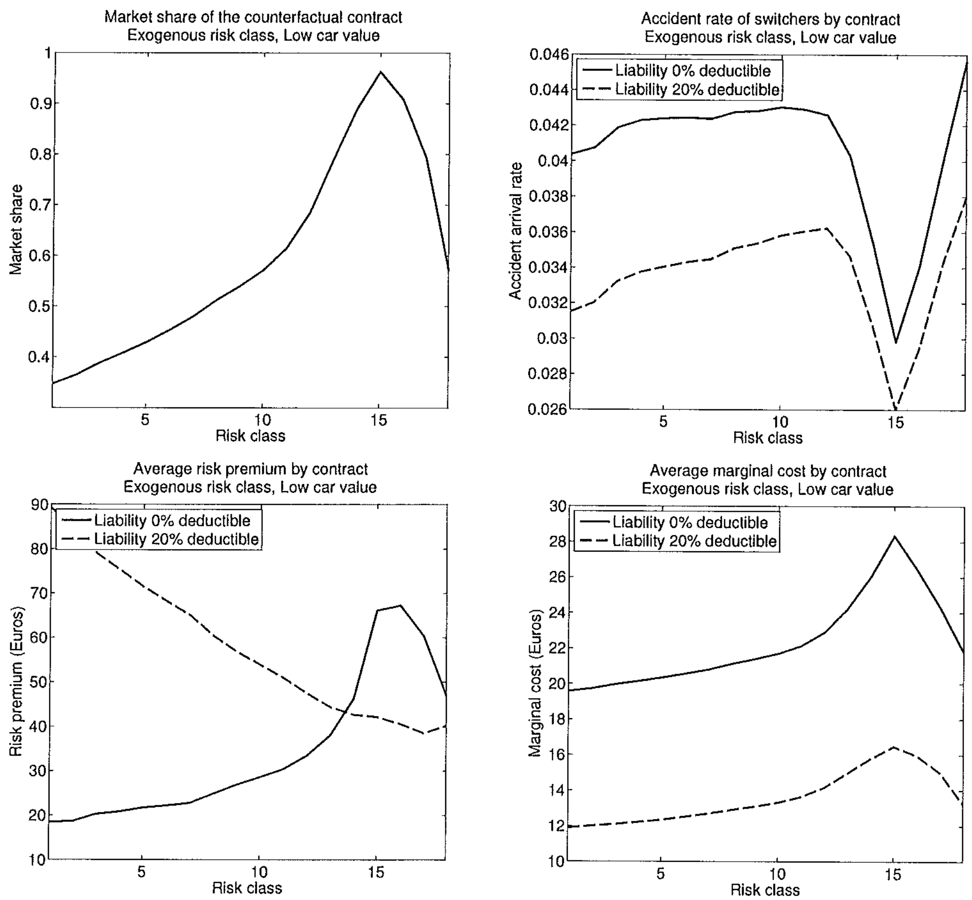


Figure 7 depicts the average risk premium and marginal costs of effort (again defined as above) for the individuals who chose the full liability coverage and the liability coverage with the deductible set at 20% of individual's car value. The graphs thus reflects sorting into the contracts on the risk aversion and the cost of effort. As the graph indicates the contract with deductible attracts individuals with lower cost of adjusting effort uniformly across risk classes. The first graph in the second panel explains this regularity. Upon choosing the contract with deductible these individuals also reduced their risk below the position they would have taken had they chosen the full liability coverage. Indeed these individuals chose lower coverage exactly because by adjusting their risk they were able to reduce their risk exposure to the level where the contract with the deductible (and lower premium) appeared more attractive then the full liability coverage.

The marginal cost graph indicates that attractiveness of the contract with liability increases with risk class (up till class 15). Recall that the premium schedule for the contract with the deductible is equal to the premium schedule of the contract with full liability coverage net of additive discount. Thus, as the risk class increases so are the incentives for the risk provision even in the full liability contract which makes it easier for individual (holding his risk aversion fixed) to achieve the level of risk which makes partial coverage attractive. In other words the contract with partial coverage attracts higher marginal cost individuals on average in higher classes.

Interestingly, sorting on risk aversion is more complex. The contracts with full and partial liability coverage present an interesting tradeoff from the point of view of risk aversion. The full liability contract offers higher coverage and is thus attractive to risk averse individuals. However, the partial coverage contract charges lower price and at the same time incentivizes risk reduction by exposing individuals to the risk on the margin. The individuals most prone to risk reduction are also those who are more risk averse (holding the marginal cost fixed). Interestingly, in the lower risk classes these are the individuals who find that they are able to sufficiently minimize their risk exposure so that the price reduction makes the contract with partial coverage more attractive. The selection is different in higher risk classes which tend to attract moderately risk averse individuals with highly risk averse individual choosing higher coverage.[12] This effect reflects the steep increase in the pricing schedule associated with higher risk classes and with it an important increase in risk premium expected to compensate for the increase in the risk exposure. For highly risk averse individuals the price discount offered for the contract with partial coverage becomes insufficient which drives them to select into full coverage contract. Thus, the full liability contract attracts both very risk averse (and ultimately very safe individuals) as well as individuals with high tolerance for risk (who tend to be riskier on average). Despite this fact individuals in the partial coverage

[12]This regularity is manifested in the fact that the average risk premium for individuals with partial coverage is decreasing in risk class whereas the average risk premium for full coverage contract is increasing in risk class.

contract remain less risky on average so that the classical result by Rothschild and Stiglitz (1976) holds even in this environment. However, the sorting on coverage is not monotone in risk aversion and thus is not conducive to price discrimination. This regularity is an artifact of a quadratic utility function which exhibits risk aversion which is decreasing in wealth.

To summarize, a contract with partial liability coverage is quite effective both in inducing sorting and also in incentivizing risk reduction for those individual who chose this contract.

Welfare Analysis

In this section we investigate welfare implications of offering additional contract with partial liability coverage. We consider several contracts with different levels of deductible and copay associated with several different price discounts. To maintain the constancy of additional risk exposure we assume that deductibles and copays are additive rather than multiplicative. The difference between copay and deductible is that within a given contract period an individual pays out of pocket until deductible is met and after that insurance company compensates all risk-related expenditures; in contrast, copay specifies the portion of each claim that individual should cover out of pocket. We measure the change in consumer welfare in terms of compensating variation. Specifically, we are looking for the amount individual have to be paid in order to remain indifferent between the settings with and without the contract with partial coverage. Similarly,the change in value appropriated by the insurance company is computed as an amount the company would be willing to pay per period to stay in the environment with additional contract rather than in the baseline world where only the full liability contract is offered. In this analysis we ignore possible change in administrative costs since it is likely to be of a second order importance relative to the costs associated with risk related expenses. The results of our analysis are summarize in Table 13.

Before we describe our findings a comment is in order. The company we study is able to charge substantial mark-up over the expected risk-related expenditure and thus appears to be quite profitable. The welfare exercise we consider does not aim to re-optimize industry pricing. Rather we consider a impact on the margin of offering an additional contract with partial coverage. That is why, we hold baseline pricing fixed maintaining that baseline prices most likely determines enrollment decisions. As a result, however, we are not able to find a counterfactual set of contracts which holds company profitability fixed. In all cases we consider, offering a contract with partial liability coverage reduces value to the company. Specifically, the company gives up more in price

Table 13: Welfare counterfactuals.

Contract Type	Additive Discount, (€)	Market share	Accidents per 800,000	Δ Consumer Welfare, (€)	Δ Life-time Value, (€)	Δ Total Welfare, (€)	Δ Total welfare per accident, (€)
Contracts with Deductible							
20%	6	17%	-662	276,215	-289,403	-13,188	- 19.9
20%	8	25%	-1,211	534,364	-518,060	16,304	13.5
20%	10	84%	-1,835	1,231,597	-1,308,131	-76,533	- 41.7
20%	12	93%	-1,923	2,636,124	-2,776,037	-139,912	- 72.7
20%	14	94%	-1,960	4,053,915	-4,218,411	-164,495	- 83.9
20%	16	95%	-2,005	5,476,253	-5,662,262	-186,009	- 92.8
20%	18	96%	-2,051	6,903,406	-7,095,428	-192,021	- 93.6
20%	20	96%	-2,102	7,153,439	-8,534,092	-1,380,652	-656.8
30%	6	12%	-535	208,851	-241,518	-32,666	- 61.0
30%	8	16%	-868	357,204	-390,477	-33,273	- 38.3
30%	10	21%	-1,303	574,997	-599,917	-24,920	- 19.1
30%	12	28%	-1,937	892,012	-895,137	-3,124	- 1.6
30%	14	76%	-2,633	1,560,832	-1,681,065	-120,232	- 45.7
30%	16	91%	-2,791	2,938,971	-3,185,339	-246,367	- 88.3
30%	18	93%	-2,842	4,353,720	-4,639,732	-286,012	-100.6
30%	20	94%	-2,887	5,771,722	-6,088,694	-316,972	-109.8
50%	6	10%	-431	180,253	-235,372	-55,119	-127.7
50%	8	12%	-698	293,955	-356,127	-62,172	- 89.0
50%	10	15%	-1,043	439,387	-503,681	-64,294	- 61.6
50%	12	18%	-1,432	635,201	-702,989	-67,788	- 47.3
50%	14	23%	-1,954	895,879	-951,004	-55,124	- 28.2
50%	16	28%	-2,573	1,233,446	-1,297,194	-63,748	- 24.8
50%	18	50%	-3,392	1,719,853	-1,828,978	-109,124	- 32.2
50%	20	87%	-3,752	2,971,297	-3,354,578	-383,281	-102.1
Contract with Copay							
20%	6	16%	-662	277,382	-287,567	-10,185	- 15.4
20%	8	24%	-1,176	539,339	-528,682	10,657	9.1
20%	10	75%	-1,721	1,355,424	-1,554,445	-199,021	-115.6
20%	12	89%	-1,909	2,720,439	-3,072,029	-351,589	-184.1
20%	14	92%	-1,998	4,131,020	-4,539,977	-408,956	-204.6
20%	16	93%	-2,065	5,548,003	-5,990,848	-442,844	-214.4
20%	18	94%	-2,148	6,978,005	-7,446,189	-468,184	-217.9
20%	20	95%	-2,212	7,153,021	-8,897,852	-1,744,831	-788.8

In this table 'deductible' refers to the amount individual has to cover out of pocket before he is compensated by insurance company; 'copay' refers to the amount individual has to pay out of pocket per claim. 'Life-time value' reflects the loss of value to the company from offering the contract with deductible/ copay in perpetuity for the current set of customers.

reduction than they are able to save due to the reduced coverage and because individuals reduce their risk upon switching. This appears to happen because the risk is already quite low in the system and the premiums are quite high.

In contrast, in all cases we consider consumers gain from introduction of a contract with partial coverage. As we explained above the welfare gains are mostly associated with the reduction in price which compensates for the cost of additional effort incurred in order to minimize risk exposure as well as this additional exposure. We show that gains in consumer welfare sometimes exceed the loss of value to the company leading to higher overall welfare (as in the case with a deductible equal to 20% of individual's car value which is equal to €200 for an average insuree and price reduction of €8; or alternatively for the contract with 20% copay and €8 reduction in contract price). More importantly, though an introduction of such the contract with partial coverage results in substantial reduction in the number of accidents. In the cases above the annual number of accident perpetrated by individuals associated with this insurance company is reduced by 1,176 to 2,000 and more. Even in the cases when total welfare is reduced by introduction of the partial liability contract the lost welfare per eliminated accident is quite small. In some cases it is close to €10. Thus we would expect that if the social gains associated with reduced number of accidents were taken into account the overall welfare would be increased.

The main welfare gains associated with introduction of partial liability coverage arise because such contract exposes individuals to greater risk on the margin and thus incentivizes socially desirable reduction in accidents. Partial coverage amounts to offering catastrophic insurance while asking individuals to cover small losses out of pocket.

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