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

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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

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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 of driving.

Driving a car exposes individual to risk of 'at fault' accidents[1] and specifically to the risk of damage to his car or health.[2] At the beginning of each period he decides whether to stay with basic liability coverage or to purchase comprehensive coverage that (up to a small deductible) protects him from the risk of damages to his own car. The individual additionally decides on the parameter λ_t which controls the distribution of the number of "at fault accidents" and, thus, individual's risk exposure. Individual's decisions reflect his risk aversion and his cost of maintaining a given level of idiosyncratic risk summarized by parameters $(\gamma; \theta)$ 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

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

[2]Recall, that insurance coverage for the third-party damages (liability coverage) is mandatory by law. We ignore "not at fault" accidents since losses associated with such accidents are covered by the liability coverage of "at fault" party. The damages to the third party car or health from "at fault" accidents are covered by own liability contract.

switching costs. The results are available from authors upon request.

Risk Exposure. 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 under "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 by $\bar{L}_t$ with $L_{r,t}$ reflecting damage from accident r. The number of accidents follows Poisson distribution with parameter λ_t chosen by individual.[3] In accordance with previous literature we assume that the distribution of $L_{r,t}$ is independent of λ. We use function $C(R, \bar{L}; y, \lambda)$ to summarize individual's risk exposure if he chooses contract y and the level of risk λ. Specifically,

$$C(R, \bar{L}; y, \lambda) = \begin{cases} R\bar{C} + \sum_{r=1}^{R} L_r & \text{if } y = y^L \\ R\bar{C} + \sum_{r=1}^{R} \min\left\{L_r, D\right\} & \text{if } y = y^C \end{cases}$$

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

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 $0 \leq \lambda \leq 1$, $\Gamma'(\lambda; \theta) \leq 0$.

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]

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.

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[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 damage to own car; and, (c) type 3: 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.

[4] In addition, we allow for the possibility that beyond some potentially large parameter $\bar{\lambda}$ the curvature of the cost function and thus the slope of the marginal costs to become steeper than is prescribed by the functional form above. This is so that increasing risk beyond certain level is difficult unless individual engage in perverse driving behavior or suffers from serious health problems.

Our model does not nest the case of 'no moral hazard' in a sense that adjustment of risk is possible at all non-zero risk levels. However, the model is capable of characterizing environments where risk adjustments in response to incentives are very small. Such outcomes arise, for example, when $\Gamma''(\lambda;\theta)$ is sufficiently large.[5]

Contract Pricing.

Insurance contract pricing is based on experience rating. Individual is assigned to a liability and comprehensive risk class 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.

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

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

where $\bar{w}$ is a constant and π represents all monetized payoff associated with car insurance market. The payoff in a given period is a function of the realized risk, contract and risk levels chosen by individual and of his risk classification. Specifically,

$$\pi(R, \bar{L}; y, \lambda, M) = -p(y, M) - C(R, \bar{L}; y, \lambda) - \Gamma(\lambda; \theta).$$

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. We assume that components

[5] In practice, even moderate values of $\Gamma''(\lambda;\theta)$ may generate negligible risk adjustments.

of s follow exogenous Markovian processes:

$$M_{t+1} = f_M(R_t, M_t)$$
$$\theta_{t+1} \sim F_\theta(\cdot|\theta_t, \gamma).$$

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 $t \in \{1, ..., T\}$

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

where τ is the stopping time, reflecting exogenous exit.[6]

The Bellman equation for the above problem is given by

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

with a terminal condition $V_T = 0$.

Discussion

The 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 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 for various classes. 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 (see, for example, Abbring, Chiappori, and Zavadil, 2011), e.g hyperbolic cost function with an asymptote ($\frac{\theta_{1,i}}{\lambda-\theta_{2,i}}$, with $\theta_{2,i} > 0$) and constant risk aversion preferences, are not capable of generating accident patterns observed in the data. Specifically, they are not capable of explaining high responsiveness of individuals

[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.

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 risk aversion maybe related to his overall wealth/income. 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 is capable of capturing cross-sectional impact of wealth/income on individual' risk aversion. Indeed, the specification we use is a reparameterized version of the following within-period utility function

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

where w_i denotes individual's wealth. In our context this should be interpreted as wealth cathegory which stays permanent during individual's driving career. Under such reparameterization all information related to individual's risk aversion (his wealth, w_i and quadratic coefficient, $\tilde{\gamma}_i$) are summarized by a single utility parameter, $\gamma_i = \frac{\tilde{\gamma}_i}{1-2w_i\tilde{\gamma}_i}$.[7] In fact, since insurance company also lacks information on individual's wealth, coefficient γ 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 $(\gamma, \theta_1, \theta_2)$.

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 expe-

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

rience, 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 .

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						

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 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 (≤ 5 years)	629	0.061	0.245		
Liability Contract Only					
All Drivers	11,252	0.036	0.192		
Young Drivers (≤ 5 years)	503	0.062	0.249		
Comprehensive Contract					
All Drivers	1,324	0.043	0.203	0.076	0.282
Young Drivers (≤ 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.

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 character-

Table 4: Statistics Related to Contract Choice

	Liability			Comprehensive		Car Value	
Risk Class	Obs	Base Premium	Adjusted Premium	Obs	Adjusted Premium	Liability Contract	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

istics, 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

Variables	Number of Liability Claims (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,

[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.

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 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 $(\sigma_\gamma^2, \sigma_{\theta_1}^2, \sigma_{\theta_2}^2, \sigma_{\gamma,\theta_1}, \sigma_{\gamma,\theta_2}, \sigma_{\theta_1,\theta_2})$, and parameters characterizing learning process (θ_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 $(\tilde{\gamma}, \theta_{1,i}, \theta_{2,i}^{low})$. Specifically,

[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.

for each individual, we draw a finite number of parameters $(\tilde{\gamma}, \theta_{1,i}, \theta_{2,i}^{low})$. Then, for each draw we solve the dynamic programming problem, and analytically integrate the moments conditional on $(\tilde{\gamma}, \theta_{1,i}, \theta_{2,i}^{low})$ for the optimal paths, starting at $t_i = 1$ (the year individual started to drive). We 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:

$$\mathbf{1}(R^L_{i,t-1} = 0) \times \mathbf{1}(R^L_{i,t} = 0) \times \mathbf{1}(K^L_{i,t-1} = 1).$$

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

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.

6.1 Parameter Estimates

Our results indicate that the model with risk adjustment proposed in the paper is capable of rationalizing available data. Indeed, the estimated parameters reported in Table 6 are of reasonable magnitudes, 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 varies across locations and is increasing in wealth (as proxied by the car value).[12]

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 47% 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 95% 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 the accident rate.

[12]This 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.

Table 6: Parameter Estimates

	Estimates	Std. Errors
Cost of Effort, Scaling Parameter (θ_1):		
Constant	1.08***	0.159
Medium car value	0.270	0.318
Large car value	0.57***	0.139
Zip code 1 and 2	-0.40***	0.130
Zip code 3	-0.32**	0.153
Female	0.15*	0.083
Cost of Effort, Reciprocal Parameter (θ_2)	7.27***	0.747
Learning:		
Cost multiplier	2.42***	0.16
Probability of learning	0.47***	0.018
Risk aversion, (γ):		
Constant	8.45***	0.006
Car value (linear term)	1.86***	0.003
Zip code 1 and 2	-0.87***	0.307
Zip code 3	0.26***	0.002
Female	0.36***	0.083
Young Driver	-0.020	4.211
Higher Order Parameters:		
σ_{θ_1}	0.20***	0.072
σ_{θ_2}	1.98***	0.251
$\sigma_{\gamma,LM}$	1.23***	0.005
$\sigma_{\gamma,H}$	0.97***	0.190
ρ_{θ_1,θ_2}	0.000	0.000
$\rho_{\theta_1,\gamma}$	-0.55**	0.239
$\rho_{\theta_2,\gamma}$	0.65***	0.003

This table reports the estimated parameters of the model. Designation 'Young driver' applies to drivers who are less than 21 years old. The variance of the distribution of risk aversion parameter is estimated for low or medium car value ($\sigma^2_{\gamma,LM}$) and for high car value ($\sigma^2_{\gamma,H}$) separately.

Table 7 reports some implied magnitudes associated with risk production and attitude towards risk. The estimates imply that an average accident rate equal to 0.082 with the standard deviation 0.034.[13] These estimates indicate that idiosyncratic risk varies importantly across individuals in this environment. We will assess the role played by private information in generating such variability in risk in the section after the next one.

Further, we compute a measure that for each individual reflects marginal cost of changing the rate of accidents from population average (0.082) by one percentage point. The distribution of this measure is thus informative of the variability of the cost of effort in population. Additionally,

[13]Note that these numbers characterize all 'at fault' claims (i.e., both liability and comprehensive).

Table 7: Some Implied Measures

	Unconditional Statistics			Unobserved Components	
	Mean	Standard Deviation	Coefficient of Variation	Standard Deviation	Coefficient of Variation
Accident rate	0.082	0.034	0.415	0.025	0.302
Marginal cost	33.042	15.989	0.484	7.679	0.232
Risk premium	73.950	122.541	1.657	83.024	1.123

This paper reports implied values for the variables determining individual's choice of risk level. 'Marginal Cost' reflects individual-specific cost of changing rate of accidents from population average (0.082) by one percentage point. 'Risk Premium' summarizes an amount individual would be willing to pay in access of the expected loss to avoid all risk to his car associated with an average rate of accidents.

for each individual we compute a risk premium this individual would be willing to pay in access of the expected loss to avoid the risk to his car associated with an average rate of accidents. 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 interest of briefness we refer to the measures described above as 'marginal cost' and 'risk premium.'

The results indicate that the cost of reducing the risk by one percentage point on average is equal to €33 with the standard deviation of €16. It is comparable in magnitude with €24 average risk exposure (average comprehensive claim $\times$ reduction in risk=€2418 $\times$ 0.01) associated with 0.01 chance of accident. Drivers in this population are willing to pay risk premium of €73 on average to avoid risk to their car associated with average accident rate. The 'back of the envelope' calculation indicates that an expected risk exposure is about €2418 $\times$ 0.08 = 192. An average individual is thus willing to pay 38% extra in order to avoid such risk. This reflects an substantial degree of risk aversion. Further, the risk premium has a standard deviation of €123 in the population indicating that important fraction of drivers are very risk averse.

6.2 Model Fit

Our results indicate that the model fits data quite well. Table 8 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 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.

Table 8: Model Fit

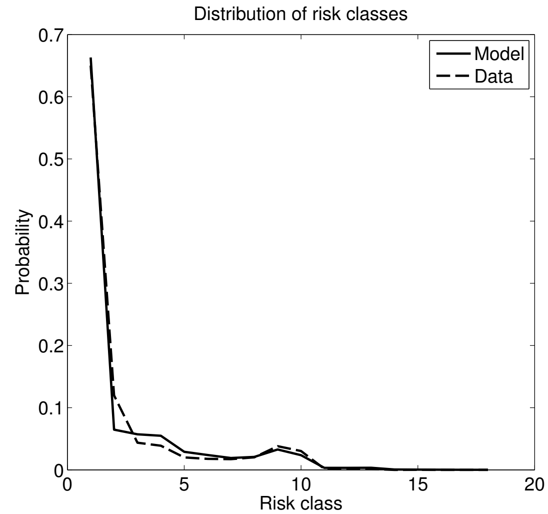
	Model	Data
Market Share of Comprehensive Contract		
overall	0.123	0.113
conditional on		
low car value	0.009	0.008
medium car value	0.061	0.052
high car value	0.413	0.396
Average Number of Liability Claims Conditional on		
liability contract	0.041	0.040
comprehensive contract	0.049	0.044
low car value	0.042	0.042
medium car value	0.045	0.044
high car value	0.039	0.036
0-3 years experience	0.080	0.079
3-5 years experience	0.047	0.047
liability risk class 1	0.039	0.036
liability risk class 2-4	0.042	0.044
liability risk class 5+	0.041	0.040
Std. Dev. Number of Liability Claims Conditional on		
liability contract	0.203	0.203
comprehensive contract	0.222	0.206

This table summarizes fit of the model to the data. It reports the actual and predicted market share of comprehensive contract in the sample and conditional on covariate values as well as actual and predicted average number of liability accidents conditional on the type of the contract and other covariate values.

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 many individuals selecting this contract especially for some values of covariates (such as low car value). Further, it appears that a flexible functional form for the cost of effort and utility function is needed 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, they are possibly not flexible enough to completely capture variability in accidents across individuals and in response to various incentives.

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.

Figure 1: Distribution Over Risk Classes



This figure plots the empirical and simulated distribution of individuals across liability risk classes.

6.3 Determinants of Risk: Cost versus Risk Aversion

Table 9 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. We perform this analysis conditional on driving experience in order to capture the effects of learning and sorting which occur over time. In simulations we maintain independence of costs and utility parameters in order to achieve orthogonal decomposition.[14]

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. Over time importance of cost heterogeneity diminishes (as it is reduced through learning) and importance of risk aversion increases.

[14]The fractions of varience explained by costs and risk aversion do not always sum up to one in the table due to the simulation error.

Table 9: Risk Decomposition

Years Driving	Avg. λ	Baseline Variance	Baseline (Coef of Var)^2	Homogenous marginal cost Variance	Homogenous marginal cost (Coef of Var)^2	Homogenous risk aversion Variance	Homogenous risk aversion (Coef of Var)^2
1	0.118	0.0012	0.083	0.00008 (-93%)	0.006	0.00106 (-9%)	0.076
3	0.081	0.0009	0.129	0.00012 (-86%)	0.019	0.00072 (-15%)	0.109
5	0.070	0.0008	0.165	0.00015 (-82%)	0.030	0.00063 (-22%)	0.128
10	0.070	0.0008	0.163	0.00016 (-79%)	0.033	0.00059 (-25%)	0.122
20	0.070	0.0008	0.161	0.00017 (-79%)	0.034	0.00060 (-25%)	0.120
40	0.071	0.0008	0.161	0.00017 (-79%)	0.034	0.00060 (-25%)	0.120

This table reports the results of the simulation study which analyses contributions of heterogeneity in maginal costs and in risk aversion to the variability of idisyncratic risk.

6.4 Importance of Asymmetric Information

Table 10 reports the estimated distribution of individual cost and utility parameters. The results indicate that all three parameters exhibit non-trivial variation both unconditionally and after the influence of observable factors have been purged away.

Table 10: Estimated Distribution of Individual-level Parameters

	Mean	Std. Dev.	$\rho(\cdot,\theta_1)$	$\rho(\cdot,\theta_2)$	$\rho(\cdot,\gamma)$
Unconditional Distribution					
θ_1	1.11 (0.079)	0.40 (0.074)	1.00 (0.000)	-0.02 (0.049)	0.25 (0.098)
θ_2	6.59 (0.792)	1.93 (0.233)	-0.02 (0.049)	1.00 (0.000)	0.25 (0.052)
γ	8.54 (0.069)	1.08 (0.042)	0.25 (0.098)	0.25 (0.052)	1.00 (0.000)
Purged of Observable Variation					
θ_1	0.00 (-)	0.19 (0.051)	1.00 (-)	0.02 (0.074)	-0.43 (0.202)
θ_2	0.00 (-)	1.90 (0.233)	0.02 (0.074)	1.00 (-)	0.56 (0.012)
γ	0.00 (-)	0.92 (0.019)	-0.43 (0.202)	0.56 (0.012)	1.00 (-)

This table characterizes the estimated distribution of individual cost and utility parameters.

Specifically, the unobserved variation accounts for 23% and 73% of overall variation in θ_1 and γ respectively. Covariates used in estimation mirror information available to insurance company. Hence, these findings indicate that significant informational asymmetries related to costs and risk aversion might be present in this market.

The estimates also show that cost and utility factors are correlated to an important degree.

Interestingly, the utility coefficient reflecting individual's risk aversion has an overall positive correlation with cost factors but when the influence of observable factors is purged away the correlation with θ_1 is negative. Thus, overall individuals with low tolerance for risk tend to have high marginal costs and high sensitivity of marginal costs to adjustments in risk whereas conditional on observables low risk tolerance is associated with low marginal costs but still high sensitivity to risk adjustments.

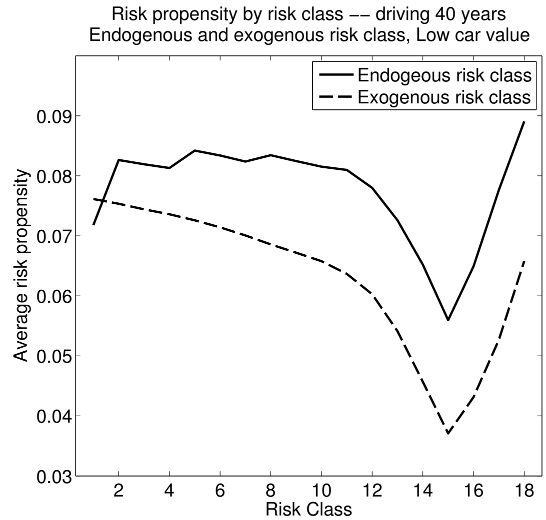
A second look at table 7 indicates that unobserved variation in costs and risk aversion translates into significant unobserved variation in idiosyncratic risk. Specifically, close to 50% of the variation in risk across individuals comes from the factors unobserved by the insurance company. Thus we find substantial variation in unobserved risk (the coefficient of variation is 0.3) in contrast to findings of the earlier literature that either failed to reject the hypothesis of 'no asymmetric information' (Chiappori and Salanie (2000)) or found very small levels of private risk variation (Cohen and Einav (2007)).

6.5 Impact of Risk Provision Incentives

In this section we assess the magnitudes of risk adjustments prompted by dynamic considerations associated with contract pricing across risk classes and static considerations related to the variation in the degree of coverage.

We begin with incentives imbedded into experience rating. To abstract away from additional complications related to sorting into contracts we focus on the drivers with low car value who predominantly (with probability 99%) choose liability only contract. At the end of our discussion we comment on the differences between the low and medium or high car value drivers. Figure 3 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. In this exercise we assume that after being randomly allocated into the risk class an individual correctly takes into account the probabilities of transition across risk classes upon having an accident and the monetary implications associated with such transition. We disregard learning and evaluate individual's behavior on the basis of his low (long-run) marginal cost of effort. The figure shows that the 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 0.02. The chosen levels of risk increase after risk class 15. The price incentives disappear at this point since individual is

Figure 2: Risk Provision Across Classes



This figure shows an average of accident rates chosen by agents with low car value under exogenous and endogenous allocation into risk classes. The endogenous allocation graph reflects sorting into risk classes in the long run (after 40 years). We focus on low car value to isolate behavior under liability costract since agents with low car value very rarely choose comprehensive coverage.

always guaranteed the placement in class 16 by the law.

Table 11 quantifies these responses. It indicates that on average individuals are quite responsive to the incentives. Specifically, an average individual reduces his risk by 4% when he is moved from class one to class five, and by 13% 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 almost by 30% 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 standard deviation of the risk rates range between 0.026 to 0.028 which constitutes 30% to 50% of the average risk.

The choices of agents with medium or high car values resemble the choices made by agents with low car values. The main difference is that individuals with higher car values have higher risk exposure under liability contract (since risk is proportional to car value). They also tend to be more risk averse. As a result such individuals generally choose lower levels of risk on average. Additionally, their chosen risk levels vary across risk classes to a lesser degree (from 0.049 in class one to 0.03% in class ten).

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

Table 11: Risk Provision Across Classes

	Allocation					
	Exogenous			Endogenous		
Risk Class	Mean Accident Rate	Relative to Class One	Std. Dev. Accident Rate	Mean Accident Rate	Relative to Class One	Std. Dev. Accident Rate
1	0.076		0.025	0.063		0.039
2	0.075	-0.013	0.026	0.083	0.317	0.023
3	0.074	-0.026	0.026	0.074	0.175	0.03
4	0.074	-0.026	0.026	0.068	0.079	0.033
5	0.073	-0.039	0.026	0.073	0.159	0.03
6	0.071	-0.066	0.027	0.069	0.095	0.032
7	0.07	-0.079	0.027	0.063	0.000	0.033
8	0.069	-0.092	0.027	0.068	0.079	0.031
9	0.067	-0.118	0.028	0.066	0.048	0.031
10	0.066	-0.132	0.028	0.064	0.016	0.03
11	0.064	-0.158	0.028	0.067	0.063	0.029
12	0.06	-0.211	0.028	0.065	0.032	0.028
13	0.054	-0.289	0.028	0.061	-0.032	0.027
14	0.046	-0.395	0.027	0.057	-0.095	0.026
15	0.037	-0.513	0.025	0.051	-0.190	0.024
16	0.043	-0.434	0.027	0.061	-0.032	0.022
17	0.053	-0.303	0.028	0.072	0.143	0.019
18	0.066	-0.132	0.028	0.082	0.302	0.015

This table quantifies the agent's response in terms of chosen accident rates to the incentives imbedded in experience rating. Numbers reflect decisions of individuals with low car values. The endogenous allocation graph reflects sorting into risk classes in the long run (after 40 years).

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 where experience-based pricing punishes them with extreme incentives so that in equilibrium their risk is substantially below the risk of more flexible individuals. We will study importance of sorting in more detail in the next section.

Table 12: Risk Provision Across Contract

Allocation	Liability Contract	Comprehensive Contract
Exogenous	0.037	0.089
Endogenous	0.045	0.067

This table summarizes the risk levels chosen by agents with high car values under different levels of insurance coverage.

Next, we take a look at the risk choices across different levels of coverage. Table 12 summarizes risk levels for the population of drivers with the high car values (who choose comprehensive coverage with probability 0.42). The table indicates that difference in coverage may induce strong response in the choice of risk levels. Indeed, comprehensive coverage results in more than twice as high levels of risk relative to the liability only coverage under exogenous allocation. However, under endogenous allocation the difference is less striking since individuals who select into comprehensive coverage tend to have lower tolerance for risk and thus are likely to aviod inceasing accident rates too much.

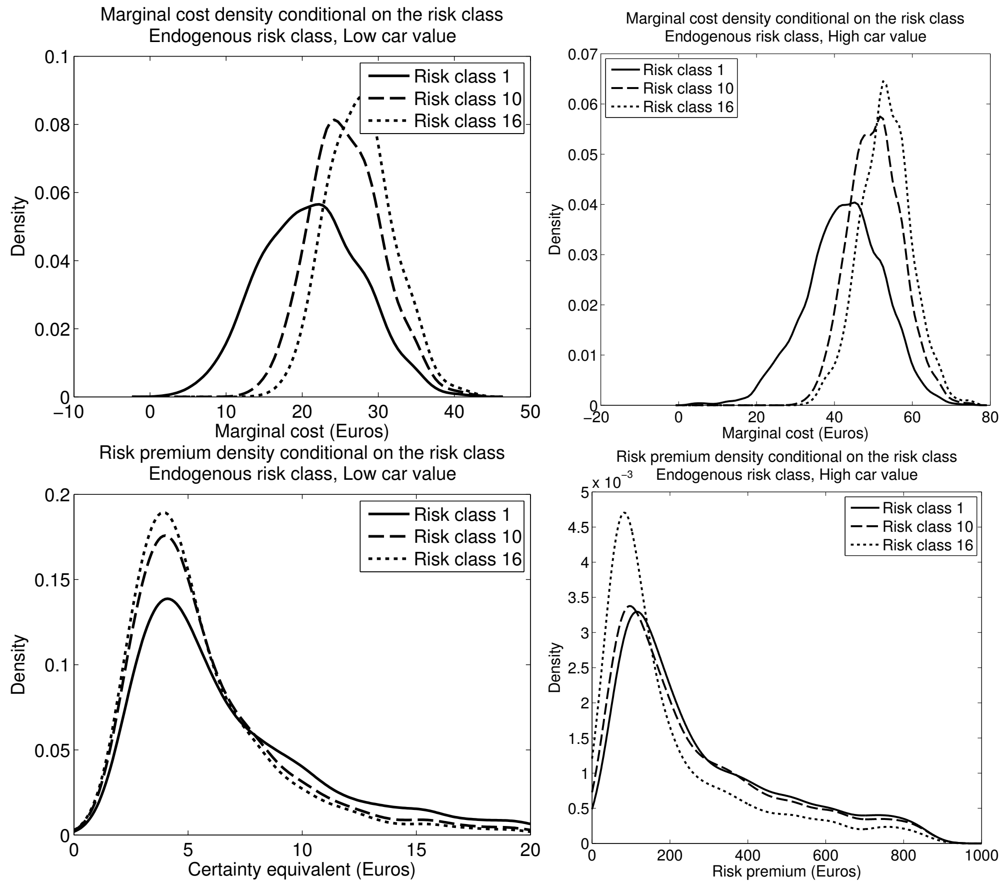
We investigate the magnitudes of sorting induced by experience rating next.

6.6 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.

In figure 3 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

Figure 3: Sorting across Risk Classes

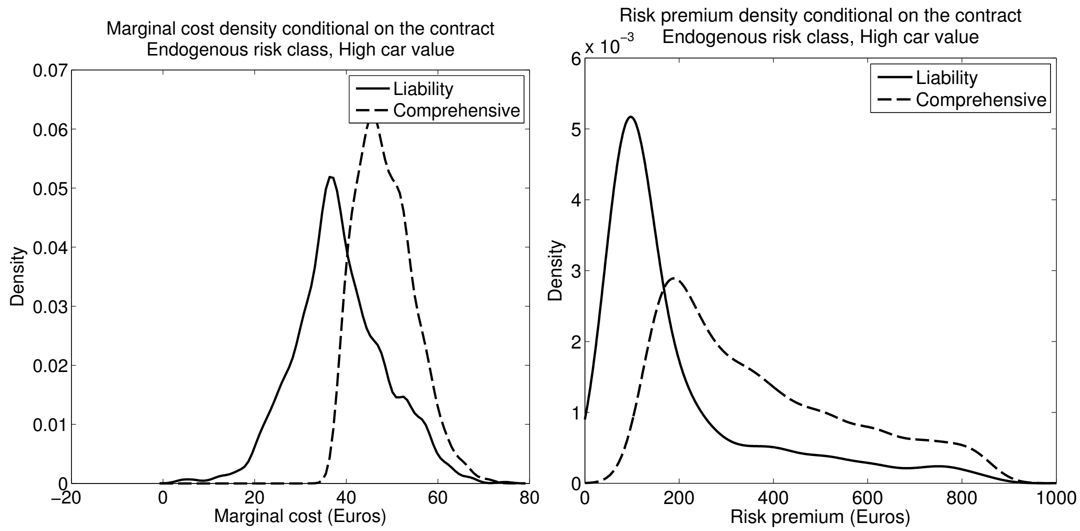


This figure demonstrates sorting into risk classes of the basis of marginal cost of effort and risk premium. It plots the distributions of these factors for the individuals who endogenously reached classes 1, 10 or 16 in the long run (left panel shows the distributions for individuals with low car values and the right panel shows the distribution for individuals with high car values.

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 premium 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 realizations 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 high risk manage to reach lower classes undetected.

Further confirmation of this regularity can be found in the Table 13. To generate this table we have chosen an individual who is average on the basis of his observables (he is a men of 30 years

Figure 4: Sorting across Contracts



This figure demonstrates sorting across contracts on the basis of marginal costs of effort and risk premium. It shoes the distribution of these factors among individuals who chose liability and comprehensive contracts respectively.

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 13 reports an explanatory power (R^2) of the regression relating individual's marginal cost, his risk premium, and his "inherent riskiness" to the liability risk class he finds himself in after a certain number of years and to the indicator of whether he chooses comprehensive coverage. We measure inherent riskiness as the level of risk he would choose in class one under exogenous allocation. This measure can be seen as a one-dimentional index of individual primitives that reflects his potential riskiness but abstracts from endogeneity of risk levels. As can be seen from table 13 the placement in a given risk class provides very little information about individual's unobserved cost, risk aversion or inherent riskiness.

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 somewhat less pronounced then in the case of the low car values. The distribution of marginal costs appears to be almost identical for classes 10 and 16. The sorting on risk aversion across risk classes appears to be somewhat

Table 13: Measuring Sorting

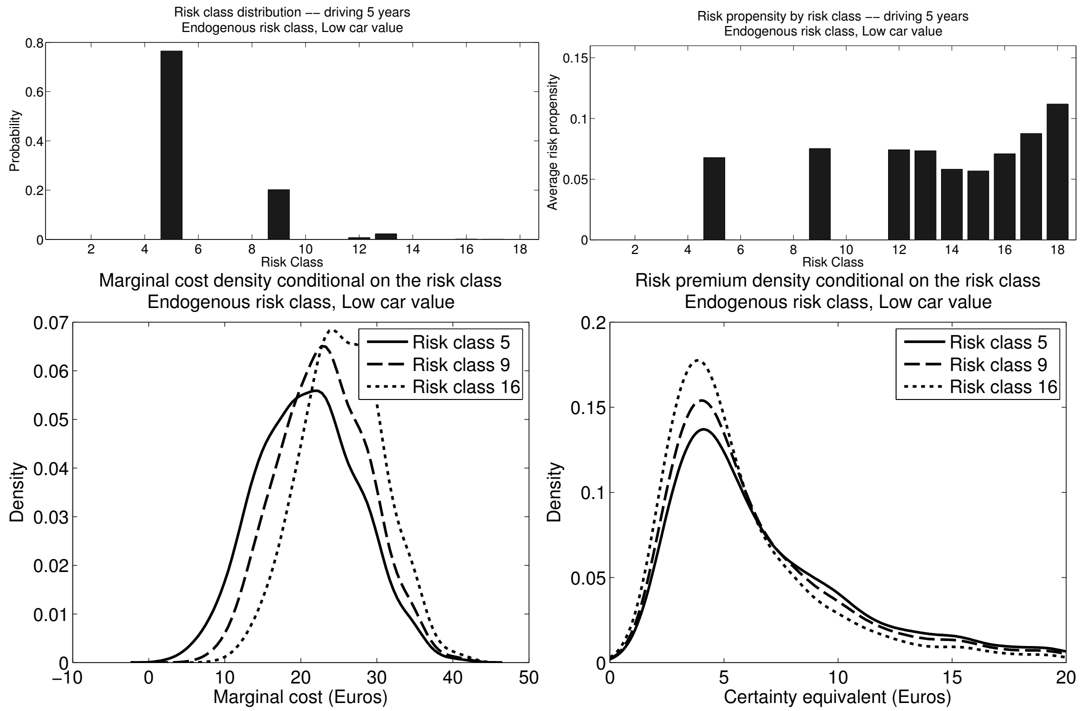
Driving Years	Included Variables	Marginal Cost	Risk Premium	Risk in Class 1
Low Car value				
1 year	Risk class (RK)	0.006	0.001	0.005
3 years	Risk class (RK)	0.015	0.002	0.016
5 years	Risk class (RK)	0.024	0.003	0.026
10 years	Risk class (RK)	0.048	0.006	0.057
40 years	Risk class (RK)	0.017	0.003	0.022
High Car value				
1 year	Risk class (RK)	0.002	0.002	0.001
	RK + Compr. contract	0.002	0.002	0.001
3 years	Risk class (RK)	0.004	0.005	0.004
	RK + Compr. contract	0.005	0.006	0.004
5 years	Risk class (RK)	0.007	0.008	0.008
	RK + Compr. contract	0.027	0.079	0.016
10 years	Risk class (RK)	0.025	0.010	0.029
	RK + Compr. contract	0.118	0.296	0.203
40 years	Risk class (RK)	0.016	0.000	0.026
	RK + Compr. contract	0.112	0.309	0.213

This table reports R^2 of the regression relating individual's marginal cost of effort, the risk premium and the level of risk individual would choose if he were exogenously placed in class one to the liability risk class he sorts into after a certain number of years and to the indicator of whether he chooses comprehensive coverage.

more important. Figure 4 documents sorting across contracts for individuals with high car values which appears to be more significant. Turning again to the Table 13 we can see that in the long run the contract choice has significantly higher predictive power than the risk class allocation. This regularity holds for all three measures. Thus, differential coverage is more effective in sorting individuals on their unobserved factors.

Intuitively, selection into contracts (or into risk classes) reduces variance of the individual factors (and therefore the variance of the error term) within seperate groups. Thus, the smaller is the largest variance of the corresponding factor across such groups the higher is R^2. Since selection into contracts is associated with partitioning of the support it results in a substantial reduction of variance. In contrast, experience rating does not lead to support partitioning. Further, most of individuals in a given cohort are always located in the lowest class. Thus, the variance of explanatory error is as large the variance of the corresponding factor in the lowest class which is very close to the variance of this factor in the population.

Figure 5: Short-Term Sorting: 5 years



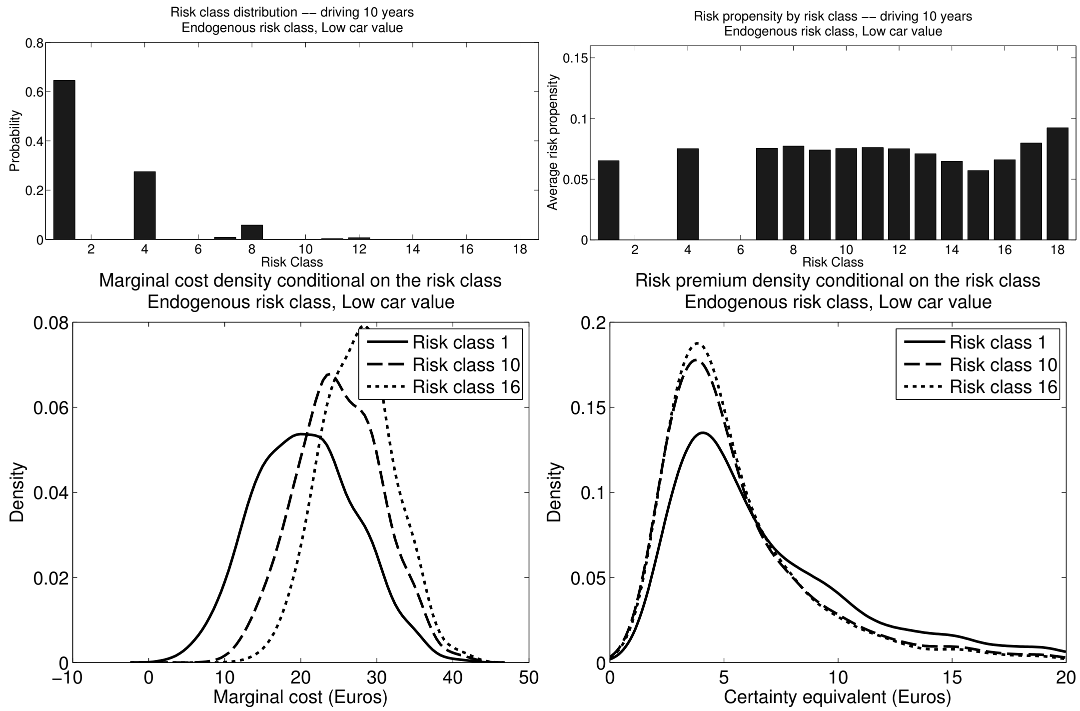
This figure demonstrates sorting into risk classes after five years of driving experience. The left graph in the top panel shows the distribution of this cohort across classes; the right top panel shows the levels of risk chosen by individuals in different risk classes; the bottom panel shows the distributions of marginal cost of effort (left) and the risk premium (right) for individuals in classes 5, 10 and 16 respectively.

We also investigate sorting in the short run: after individuals have been driving for one, three, five or ten years. Figures 5 and 6 and Table 13 illustrate the information acquisition within this time frame. As can be seen by comparing figure 5 and 6 more information is revealed with time. However, even after five or ten years very little sorting across classes has occurred. This is confirmed in Table 13. 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 cost of effort- and risk aversion-related factors have implications for contract design. Specifically, when deciding on contract

Figure 6: Short-Term Sorting: 10 years



This figure demonstrates sorting into risk classes after ten years of driving experience. The left graph in the top panel shows the distribution of this cohort across classes; the right top panel shows the levels of risk chosen by individuals in different risk classes; the bottom panel shows the distributions of marginal cost of effort (left) and the risk premium (right) for individuals in classes 5, 10 and 16 respectively.

terms an insurance company may emphasize dynamic pricing based on experience rating or offer a more extensive menu of static contracts. The first strategy will incentivising risk reduction whereas the second strategy will be effective in screening customers on risk and thus will allow to price risk more precisely. It is worth noting that static contracts may also provide incentives for risk reduction when they offer reduced coverage and thus expose customers to more risk on the margin.

Historically, European companies have been legally prevented from incentivizing risk reduction through static 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 potential welfare costs of this law. We consider a counterfactual world where a partial liability contract is offered in addition to the full liability and comprehensive coverage that offered in real world. We implement such partial in a form of a deductible that individual has to pay out of pocket with the size of the deductible tied to the individual's car value. We leave the price of full liability contract unchanged since it most likely determines enrollment decisions. The price of a new contract is set equal to the price of a full liability contract minus additive discount (held constant across risk classes).

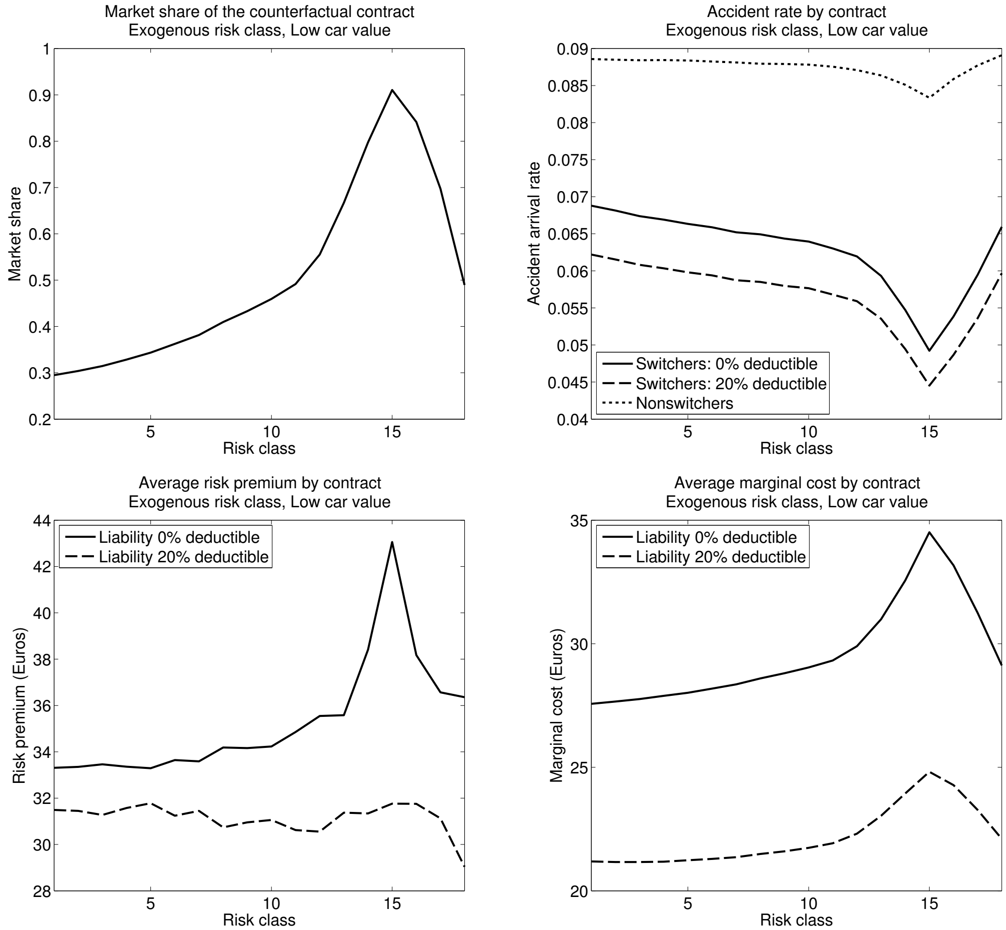
7.1 Drivers' Choices under Counterfactual Menu of Contracts

We begin by investigating decisions of individual drivers who are faced with such alternative menu of contracts. This analysis focuses on the subset of drivers with low car values since the choice between the full and partial liability coverage is most relevant for this group. The drivers with high car values have much higher risk exposure and thus tend to choose either full liability or comprehensive coverage.

Figure 7 illustrates selection and chosen levels of risk. We construct these graphs by exogenously associating individuals with risk classes as in section 6.5 to abstract away from endogenous sorting associated with experience rating. We maintain, however, that agents expect their risk classes to be adjusted according to the rules of experience rating in the future. They may also reconsider their choice of contract each period. Hence, we have a non-selected population associated with each risk class and all individuals in a given class face the same consequences of having 'at fault' accident regardless of the contract they choose.

The lower panel of figure 7 depicts the average risk premium and marginal costs 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 reflect sorting into the contracts on risk aversion and marginal cost of effort. The contract with deductible attracts individuals with lower cost of effort uniformly across risk classes. The first graph in the top panel explains this regularity. Upon choosing the contract with deductible these individuals reduce their risk below the position they would have taken had they chosen the full liability coverage. Indeed these individuals choose lower coverage because by adjusting their risk they are able to reduce their risk exposure to the level where the contract with the deductible (and lower premium) becomes 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, the incentives for the risk provision inrease with the risk class 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

Figure 7: Implications of Partial Liability Coverage



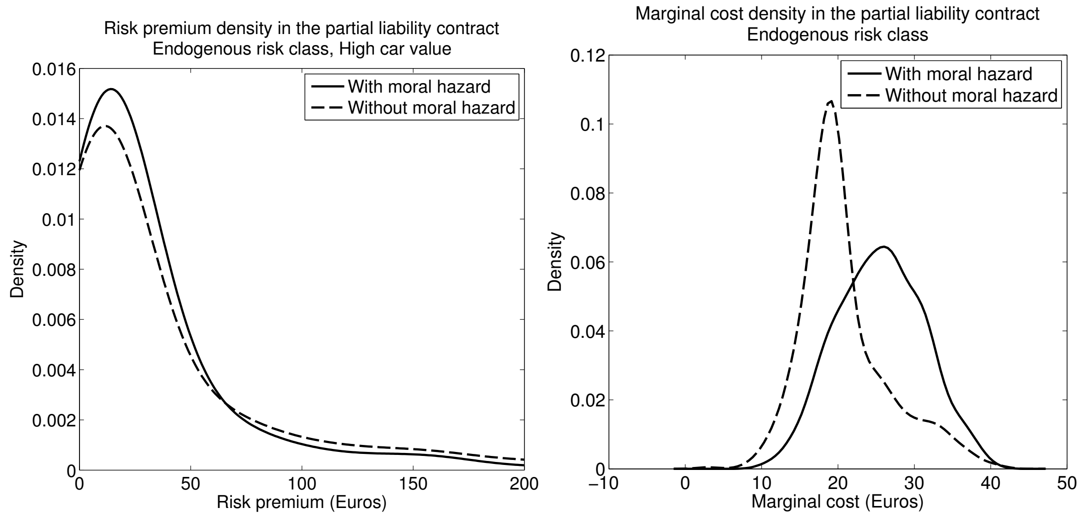
These figures illustrate sorting into contracts and the levels of risk chosen by drivers when faced with a menu of contracts which includes partial liability contract. The top panel shows the share of low car value drivers who chose partial liability coverage and the levels of risk chosen by different subsets of drivers. The lower panel depicts the average risk premium and the average marginal costs for the groups of drivers who choose different coverage.

attracts higher marginal cost individuals on average in higher classes.

Further, the left-hand side graph in the lower panel indicates that the contact with partial coverage attracts individuals with higher tolerance for risk. This is not surprising since these individuals require lower compensation for taking on extra risk. Interestingly, this effect qorks agaist the one described above since these individuals are also less prone to adjust their risk in response to the incentives. That is why, switching is associated only with moderate adjustment of risk levels.

Figure 8 illustrates the impact of risk adjustment on sorting into the contract with partial liability coverage. Specifically, it graphs the distribution of the risk premiums and marginal costs for two cases: (a) when agents are allowed to adjust risk as in our baseline model; (b) when

Figure 8: Comparing Adustable and Fixed Risks



These figures illustrate sorting into partial liability contract under the baseline model (with adjustable risk) and the case when the risk of each driver is fixed at the level he would have chosen in the risk class one under exogenous allocation.

agent's risk is fixed at the level he would have chosen under a standard menu of contracts (which includes only full liability and comprehensive coverage). The graphs illustrates that selection is more pronounces in the later case since only individuals with sufficiently low (fixed) levels of risk would chose partial coverage. In contrast, with risk adjustment a larger set of agents prefers partial coverage. In includes not only individuals who choose sufficiently low risk under full liability coverage but also those who can reduce their risk to the level which makes partial coverage attractive.

7.2 Welfare Analysis

In this section we investigate welfare implications of offering additional contract with partial liability coverage. We consider several contracts with several levels of deductible and copay associated with 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 for the relevant driving-related losses; 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 each period 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 14.

Before we describe our findings a comment is in order. 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. We hold the premium for full liability fixed and index the price for the partial liability contract to the full liability contract in order to minimize the possibility of the change in enrollment. 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 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 and for this additional exposure. We show that gains in consumer welfare sometimes exceed the loss of value to the company leading to higher overall welfare (e.g., with a deductible equal to 20% of individual's car value (€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 the contract with partial coverage leads to substantial reduction in the number of accidents. For example, the annual number of accident perpetrated by individuals associated with this insurance company is reduced by 1,518 for the deductlible of 20% and the price discount of €10 . 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 €30 -€40. 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

Table 14: Welfare counterfactuals.

	Additive Discount	Market share	Accidents per 800,000	Δ CS 1,000€	Δ PS 1,000€	Δ TS 1,000€	Δ TS (€) per accident
Contracts with Deductible							
20%	€6	14%	-481	254.8	-231.0	23.8	49.4
20%	€8	22%	-901	507.7	-459.4	48.4	53.7
20%	€10	46%	-1,518	971.7	-928.2	43.5	28.6
20%	€12	85%	-1,853	2,207.7	-2,411.5	-203.8	-109.9
30%	€6	8%	-308	188.0	-182.6	5.4	17.4
30%	€8	12%	-605	324.3	-304.4	19.9	32.9
30%	€10	18%	-976	535.0	-506.0	29.0	29.6
30%	€12	25%	-1,464	843.7	-797.2	46.4	31.7
30%	€14	36%	-2,102	1,299.8	-1,246.1	53.8	25.6
30%	€16	76%	-2,551	2,353.7	-2,587.2	-233.5	-91.5
50%	€6	6%	-244	164.3	-165.3	-935	-3.8
Contract with Copay							
20%	€6	12%	-442	249.8	-229.2	20.6	46.5
20%	€8	20%	-859	495.8	-468.0	27.7	32.3
20%	€10	45%	-1,435	1,002.5	-1,062.6	-60.1	-41.8

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.

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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