Estimating an Equilibrium Model of Insurance with Oligopolistic Competition

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Motivation: Public Policy

- Understanding the drivers of the demand for insurance is crucial to perform \textit{ex-ante} policy analysis evaluation.

- In order to evaluate "structural" reforms of the market, mandatory discounts, deductibles, restriction of pricing rules an explicit economic model is needed.

- A major challenge is \textit{identification}: given data on contracts and claims can we \textit{identify} the parameters of interest?

- In this paper we focus on \textit{demand} ⇒ we keep supply as given ⇒ we are extending our demand framework to an oligolistic market.

- Our counterfactual exercises are valid to the extent that companies do not react to the simulated policies.
This paper

- Estimate demand for automobile insurance.
- Insurees have heterogeneous risk and risk preference.
- Select from different insurance companies.
- With switching costs.
- Context: Italian automobile insurance.
Outline of the Talk

- Motivation
- Data
- Model
- Results on Identification
- Reduced form Evidence
- Preview of Equilibrium part
- Road Ahead
Sources of market frictions:

1. Asymmetric information:
   - Only insuree know her risk ($\theta$) and risk preference ($a$).
   - Insurance companies only know ($\theta, a$) $\sim F(\cdot | X, Z)$.
   - ($\theta, a$) function of observed insuree ($X$) and car ($Z$) covariates.
   - **Adverse selection**: better coverages attract risker drivers.
   - **Advantageous selection**: better coverages attract risk averse.
   - Net effect depends on $F(\cdot | \cdot, \cdot)$.

2. Switching cost:
   - Reduces effective competition and “locks-in” insurees.
   - Insurers “respond” by giving “new-consumer” discounts.
   - Could exacerbate adverse selection.
   - Crucial policy relevant parameters $\rightarrow$ IVASS working on TUOPREVENTIVATORE (website to get auto insurance quotes)
Questions

1 What is the welfare loss due to:
   1.1 asymmetric information; and
   1.2 switching cost?

2 What is the extent of:
   2.1 adverse selection; and
   2.2 advantageous selection?

3 How much of the observed price dispersion (across regions) is driven by:
   3.1 differences in consumer types across regions; and
   3.2 differences in switching costs?
Asymmetric information → market failure → welfare loss.
Rothschild and Stiglitz (1976) → severe adverse selection.
Chiappori & Saline (2000): $\text{corr(coverage, claim)} \approx 0$.
Found no evidence of adverse selection in French data.
Recent papers: at best mixed evidence of adverse selection.
Why? Theory is silent → truly an empirical question.
Heterogeneity in risk-preference + \( \text{corr}(\theta, a) < 0 \rightarrow \) good drivers buy high coverage \( \rightarrow \text{corr}(\text{coverage}, \text{claim}) \approx 0. \)

Private information must be multidimensional.


And recently: Aryal, Perrigne & Vuong (2016).
Most papers study the demand side, but from only one seller. Here: representative sample of Italy - oligopoly markets. How does selection among different insurers affect estimates? Given our data we can also explore:

1. Do $F(\cdot, \cdot | X, Z; \text{market})$ vary across market?
2. What fraction of dispersion in premium across regions can be explained by differences in $F(\cdot, \cdot | X, Z; \text{market})$?

Empirical: virtually none except Cosconati (2016)
Identifying Preferences for Risk: Issues

- Cohen and Einav (AER 2006) → risk aversion is more important than risk in determining demand for insurance
- → it is important to account for multiple dimensions of private information
- they identify parametrically the joint distribution of risk and risk aversion using data from one single Israeli company
- we extend their analysis in several ways
  1. distribution of risk and risk aversion is unrestricted ⇒ robustness: our results will be less dependent on the assumptions we made
  2. differentiated insurance product and multiple companies
  3. our framework and data will allow to take into account sorting into companies
  4. we can estimate and identify the true distribution of risk/risk aversion in the market as opposed to company specific distribution

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Cosconati (2016) → estimates hedonic premium regressions that are the basis of our atheoretical supply

- spells out the identification assumptions to estimate company-specific premium regressions
- substantial heterogeneity across companies in the premium-accident schedule → potential source of sorting
- company dummies are significant in the accident probability → reduced form evidence of self-selection

- companies differ in terms of the clauses offered → product differentiation can generate selection on risk

- these empirical results/arguments suggest that focusing on one company can be misleading to infer preferences for risk
In this paper

The necessary first step is to understand the demand well.

- We take the supply side as given: atheoretical supply.
- Model the demand with rich consumer unobserved heterogeneity and switching cost.
- Identification: semiparametric identification.
- To do:
  1. Estimate the model primitives using data from Italy.
  3. Counterfactuals.
In this paper

1. Exogenous coverage characteristics.
   - Model: Oligopoly + multidimensional private information + switching cost is a hard problem to solve.
   - Identification: usual “BLP instruments” are infeasible because of endogenous product characteristics.

2. Static decision.

3. No moral Hazard.
IPER consists of

- **insurance histories** of a core sample of drivers who subscribed one or more contracts in 2013 \(\Rightarrow\) the unit of observation is the SSN
- the histories contain info on multiple contracts, new vehicles and the evolution of each contract underwitten by a driver of a core sample \(\Rightarrow\) akin to the PSID/NLSY
- only info on privately owned cars \(\Rightarrow\) no trucks, motorcycles, fleet vehicles
- BIG data \(\Rightarrow\) in previous work much smaller sample size \(\Rightarrow\) a major problem when dealing with rare events
- IPER is **representative** of the market \(\Rightarrow\) info on contracts underwritten by nearly 50 companies operating in the Italian market
IPER contains info on:

- **the driver**: age, province of residence, gender
- **the vehicle**: cc, horse power, year of registry
- **clauses**: 5 clauses
- **the actual premium paid**: different than the tariff
- **claims**: number of claims and their size at fault for each contractual

These info allow to estimate *hedonic price regressions* and competition in local markets (provinces/regions)

IPER allows to analyze premiums as an equilibrium object ⇒ typically only data from one/two companies are available
Features

- Attrition rate 9.4% (4.8%) for contracts expiring 2014 and 2015, respectively.
- 735,506 contracts observed for each of the three years 2013-2016.
- 22% subscribe basic coverage for more than one vehicle, majority of those have 2 vehicles.
- 13,071 contracts in 2014 and not renewed in 2015.
- More than 30% with multiple contracts purchase coverage from multiple companies → we rationalize this by different loadings on Z across companies
Companies provide information on past: number of accidents at fault filed during the past five years.

Supplement: “Banca Data Sinistri” (BDS): the universe of claims filed in the market.

Match BDS with IPER using SSN-plate number.

Data: first three accidents (in chronological order) filed within a contractual year.

Accident date, Claim filing date, Damage size.
General Description

- Italy: basic auto insurance (rc auto) and a motor third party liability is mandatory.
- Covers damage to third parties’s health and property damage if the driver is not at fault.
- Upper limit for liability: 1 million Euros for property damage and 5 millions for health.
- Owner of the car is typically the subscriber of the insurance contract.
- Each accidents has a percentage of fault (pc) ranging from 1 to 100 percentage points.
Market Structure

- IPER: 45, 47 and 45 companies in the 1st, 2nd, 3rd.
- Market share: 1st (29.94%); 2nd (11.65%) and 3rd (11.05%).
- The largest 10 have 90% market share.
- Switching: 13.7% and 13.5% in the 2 years.
Insurees:
1. car and insuree characteristics: \((X, Z) \sim F_{X,Z}(\cdot)\).
2. unobserved heterogeneity: \((\theta, a) \sim F(\theta, a|X, Z)\).
3. \(\Pr(\text{at least one accident}) = \theta\)
4. CARA utility: \(v(w; a) = -\exp(-aw)\).
5. Random damage: \(D \sim H(\cdot|Z)\) over \([0, \bar{D}]\).

Options: \(J = \{1, 2, \ldots, J\}\) set of all options.

Insurance contract:
1. Premium-clauses pair \(\{P_j, \xi_j\}\).
2. Random indemnity: \(E \sim \Psi(\cdot|\xi_j)\).
3. All accidents in a year are “aggregated” into one.

We consider demand without switching cost first.
\[ \tilde{U}_{ij} = (1 - \theta_i) \nu(W_i - P_{ij}; a_i) \quad \text{no-accident} \]
\[ + \theta_i \lambda_j \int_0^D \nu(W_i - P_{ij} - D; a_i) dH(D|Z) \quad \text{at-fault} \]
\[ + \theta_i (1 - \lambda_j) \int_0^D \int_0^D \nu(W_i - P_{ij} - D + E; a_i) d\Psi(E|\xi_j) dH(D|Z) \quad \text{not-at-fault} \]

CRRA \quad \Rightarrow \quad \tilde{U}_{ij} = -\exp(-a_i(W_i - P_j)) \left[ 1 - \theta_i + \theta_i \left( \lambda_j \mathbb{E}_H(\exp(a_iD)|Z) \right. \right.
\[ \left. + (1 - \lambda_j) \mathbb{E}_{\Psi,H}(\exp(-a_i(E - D))|X, Z; \xi_j) \right) \right] \]
\[ \therefore \tilde{U}_{ij} \equiv \exp(-a_i(W_i - P_j)) \left[ 1 - \theta_i + \theta_i \Gamma(a_i; \lambda, H, \Psi, \xi_j) \right] . \]
Premium enters non-linearly and wealth is unobserved.

But with CARA, work with the certainty equivalence of each $j$.

The certainty equivalence of the contract $(P_j, \xi_j)$ is

$$-\exp(-a_i CE(P_j, \xi_j)) = \tilde{U}_{ij}$$

Solving for CE we get

$$CE(P_j, \xi_j; \theta_i, a_i) = -P_j - \frac{1}{a_i} \ln \left[ 1 + \theta_i \left( \frac{\Gamma(a_i; \lambda, H, \Psi, \xi_j) - 1}{1} \right) \right] = U_{ij}$$

$$\equiv -U_{ij} - P_j.$$

One dimensional insuree type: $U_{ij} \sim F_U(\cdot | X, Z, \xi)$

$U \rightarrow$ one-dimensional sufficient statistic.
Model
Random Utility Theory

- Let the preferences be represented in terms of $CE$ as
  \[ u_{ij} = CE_{ij} + \epsilon_{ij} = -\mathcal{U}_{ij} - P_{ij} + \epsilon_{ij}, \quad \epsilon_{ij} \sim T1EV \]  
  \[ (1) \]

- Then, an insuree $i$ chooses solves
  \[ j = \arg \max_{j \in J} u_{i \tilde{j}}. \]

- Thus the probability that consumers $i$ chooses policy $j$ is
  \[ S_{ij} = \frac{\exp(-\mathcal{U}_{ij} - P_j)}{\sum_{j'=0}^J \exp(-\mathcal{U}_{ij'} - P_j)}. \]

- Unconditional probability of an insuree choosing $j$ is given by a mixture
  \[ S_j(P, X, Z) = \int_{\bar{U}} S_{ij}(P, U)\, dF_U(U|X, Z). \]  
  \[ (2) \]
Data: premium, history, claims, indemnity, at-fault and \((X, Z)\)

Parameters: \(F(\theta, a | X, Z)\) and \(H(\cdot | Z)\).

Let \(D_{ij}\) be both a random variable or a vector thereof if insuree \(i\) had multiple accidents because damages are i.i.d. across insures and damages.
Identification

Heuristics

1. Identify \( \mathcal{U} \sim f_\mathcal{U} \) by inverting the (model) share of \( j \):

\[
    s_j = \int_{U} k(p) f_\mathcal{U}(u|x,z) \, du
\]

2. Identify \( \theta \sim f_\theta(\cdot|x,z) \) using Logit assumption + \# accident.

3. Use \( f_\mathcal{U}(u|x,z) \) and \( f_\theta(\cdot|x,z) \) to identify \( f_{\theta,a}(\cdot,\cdot|x,z) \).

4. Identify \( \lambda \) using Logit assumption + “at-fault” data.

5. Still figuring out how to identify \( H(\cdot|Z) \) and the distribution of indemnity \( (D - E) \).
Identification
Identification of $F_u(\cdot|X, Z)$

- Fix $(F_\theta, a(\cdot|\cdot), H(\cdot|Z), \psi(\cdot; \xi), \lambda)$.
- Normalize utility from outside option to $\tilde{U}_0 = U_{i0} - P_0$, and take ratio of the probabilities:

$$\tilde{S}_{ij} := \frac{S_{ij}}{S_{i0}} = \exp(-U_{ij} - P_j - \tilde{U}_0).$$

- Integrating this over the entire population gives

$$\tilde{S}_j(P, X, Z) = \int_u \tilde{S}_{ij}(P, U) dF_U(U_{ij}|X, Z)$$

$$= \int_u \exp(-(P_j + \tilde{U}_0) - U_{ij}) dF_U(U_{ij}|X, Z)$$

$$= \int_u \exp(-\tilde{P}_j - U_{ij}) dF_U(U_{ij}|X, Z).$$
Identification

Identification of $F_{U}(\cdot | X, Z)$

- Convolution theorem $\Rightarrow$ Laplace transform of $\tilde{S}$ is the product of the Laplace transform of $\exp(-\tilde{P}_{j} - U_{ij})$ and $f_{U}(\cdot | \cdot)$.
- Using $\mathcal{L}$ to denote the Laplace transform (suppress $(X, Z)$):
  \[
  \mathcal{L}\tilde{S}(u) = \mathcal{L}\exp(u) \times \mathcal{L}f_{U}(u) \Rightarrow \mathcal{L}f_{U}(u) = \frac{\mathcal{L}\tilde{S}(u)}{\mathcal{L}\exp(u)}.
  \]
- Now, invert the Laplace to get
  \[
  f_{U}(u) = \frac{1}{2\pi i} \lim_{T \to 0} \int_{-iT}^{iT} \exp(\xi u) \frac{\mathcal{L}\tilde{S}(\xi)}{\mathcal{L}\exp(\xi)} d\xi.
  \]
Identification of \( F_{\theta, a}(\cdot, \cdot | X, Z) \)

- There is a one to one mapping between \((\theta, a)\) and \((U, a)\)
  \[
  \begin{pmatrix}
  U \\
  a
  \end{pmatrix}
  \mapsto
  \begin{pmatrix}
  g_1(U, a) = \theta \\
  g_2(U, a) = a
  \end{pmatrix};
  \quad
  g_1(U, a) = \frac{\exp(aU) - 1}{\Gamma(a; \lambda, H, \Psi, \xi) - 1}.
  \]

- Let \( J \) is the Jacobian of \( g_1(U, a) \). Then
  \[
  f_{U, a}(U(\theta, a), a) \times |J| = f_{\theta, a}(\theta, a | X, Z)
  = f_{a|\theta}(a|\theta, X, Z) \times f_{\theta}(\theta | X, Z).
  \]

- Hence it is enough to identify the marginal density \( f_{\theta}(\theta | X, Z) \).
We exploit multiple accidents for identification.

We model the risk be a Zero-inflated Binomial process.

Let $A_i \in \{0, 1, 2, 3\}$: #accidents met by insuree $i$ with pmf

$$A_i \sim \begin{cases} 
0, & \text{with probability } (1 - \theta_i), \\
B(n_i, \pi_i), & \text{with probability } \theta_i \\
\end{cases} ; \quad \forall i, n_i \leq 3.$$

Thus

$$\Pr(A_i = 0) = (1 - \theta_i) + \theta_i (1 - \pi_i)^{n_i};$$

$$\Pr(A_i = \ell) = \theta_i \binom{n_i}{\ell} \pi_i^{n_i} (1 - \pi_i)^{n_i-\ell}, \ell = 1, 2, n_i = 3.$$
Identification
Identification of $f_\theta(\theta|X, Z)$

- Furthermore, let $\theta_i$ and $\pi_i$ be generalized linear models:
  - $\logit(1 - \pi_i) = \tilde{Z}_i \beta$ and
  - $\logit(1 - \theta_i) = \tilde{X}_i \tau$.
- $\tilde{Z} \subset Z$ car and market characteristics that affects the number of accidents and $\tilde{X} \subset X$ is the insuree characteristics (e.g., BM-class) that affect whether an insuree has an accident or not.
- Maximize log-likelihood:
  $$\log L = \sum_{i=1}^{N} \left\{ 1(A_i = 0) \log [e^{\tilde{X}_i \tau} + (1 + e^{\tilde{Z}_i \beta})^{-n_i}] - \log (1 + e^{\tilde{X}_i \tau}) ight\} + (1 - 1(A_i = 0)) \times [a_i \tilde{Z}_i \beta - n_i \log (1 + e^{\tilde{Z}_i \beta}) + \log \left( \frac{n_i}{a_i} \right)] \right\}.$$

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Define a (latent) indicator variable $\omega_i \in \{0, 1\}$ such that $\omega_i = 1$ when $A_i$ is from the zero state and $\omega_i = 0$ when it is from the Binomial state.

If we could observe $\omega_i$ then the log-likelihood can be simplified to be

$$\log L = \log \prod_i \Pr(A_i = a_i, \omega_i) = \sum_{i=1}^{N} \left[ \omega_i \tilde{X}_i \tau - \log(1 + e^{\tilde{X}_i \tau}) \right] + \sum_{i=1}^{N} (1 - \omega_i) \left[ a_i \tilde{Z}_i \beta - n_i \log(1 + e^{\tilde{Z}_i \beta}) + \log \left( \frac{n_i}{a_i} \right) \right].$$

Since $\omega_i$ is unknown, we can use Nested-Fixed Point algorithm (or EM algorithm) to estimate conditional mean of $\omega_i$ given $(\beta, \tau)$.
Identification
Identification of $\lambda$

- Fix $(H(\cdot|Z), \psi(\cdot; \xi))$
- Suppose we observe the universe of all accidents that were claimed.
- Let there be $M$ total accidents in the data with third party damages, and hence $2M$ many observations.
- For every accident we can assign an at-fault indicator $Y_i \in \{0, 1\}$ to each (involved) insuree.
- Then, $\Pr(Y = 1|X, Z, \xi) = \lambda = \mathbb{E}[Y|X, Z, \xi] \rightarrow$ the likelihood

$$\prod_{i=1}^{2M} \Pr(Y = y_i|X = x_i, Z = z_i, \xi = \xi_i)$$

$$= \prod_{i=1}^{2M} \Pr(Y = y_i|X = x_i, Z = z_i, \xi_i = \xi_j)$$

$$= \prod_{i=1}^{2M} p(x_i, z_i, \xi_i; \kappa)^{y_i} (1 - p(x_i, z_i, \xi_i; \kappa))^{1-y_i}.$$
Let $\log\left( \frac{p}{1-p} \right) = e^{\kappa_0 + \kappa_1 X + \kappa_2 Z + \kappa_3 \xi}$, so

$$\log L = \sum_{i=1}^{2M} y_i \log p(x_i, z_i, \xi_i; \kappa) + (1 - y_i) \log(1 - p(x_i, z_i, \xi_i; \kappa))$$

$$= \sum_{i=1}^{2M} -\log(1 + e^{\kappa_0 + \kappa_1 X + \kappa_2 Z + \kappa_3 \xi}) + \sum_{i=1}^{2M} y_i (\kappa_0 + \kappa_1 X + \kappa_2 Z + \kappa_3 \xi).$$
Identification of $\Gamma(a_i; \lambda, H, \Psi, \xi_j)$

Since

$$\Gamma(a_i; \lambda, H, \Psi, \xi_j) = \lambda_j \mathbb{E}_H(\exp(a_i D)|Z) + (1 - \lambda_j) \mathbb{E}_{\Psi, H}(\exp(-a_i (E - D))|X, Z; \xi_j)$$

so identifying the indemnity distribution $\Psi(\cdot|\xi)$ and the damage distribution $H(\cdot|Z)$ is sufficient.
Switching cost $\beta_i \sim F_\beta(\cdot|X)$.

Let $k(i, t)$ denote the insurance company from whom insuree $i$ bought her coverage in period $t$, and $k_j$ denote the company that sells contract $j$.

Moreover when an insuree switches company, she gets a “new customer” discount $\delta_{ij}(k)$.

Then the random certainty equivalence:

$$u_{ij} = -U_{ij} - P_j - (\beta_i - \delta_{ij}(k))1\{k_j \neq k(i, t - 1)} + \epsilon_{ijt},$$

The probability that insuree $i$ chooses policy $j(k)$ is

$$S_{ij} = \frac{\exp(-U_{ij} - P_j - (\beta_i - \delta_{ij}(k))1\{k_j \neq k(i, t - 1)})}{\sum_{j' = 0}^{J} \exp(-U_{ij'} - P_j - (\beta_i - \delta_{ij'}(k))1\{k_{j'} \neq k(i, t - 1)})}.$$
Condition on $X_i$, the discount does not vary across insuree so:

$$\delta_{ij}(k) = \delta_j(k) + \gamma X_i.$$ 

So the conditional probability that $i$ chooses $j$ is

$$S_{ij} = \frac{\exp(-U_{ij} - P_j - (\beta_i - \delta_j(k) - \gamma X_i)1\{k_j \neq k(i, t-1)})}{\sum_{j'=0}^J \exp(-U_{ij'} - P_j - (\beta_i - \delta_{j'}(k) - \gamma X_i)1\{k_{j'} \neq k(i, t-1)})}.$$ 

If $(\beta_i - \delta_j(k) - \gamma X_i) > 0 \rightarrow$ inertia in the choice of insurance company.

The conditional choice probability of repeat purchasing exceeds the marginal choice probability.

Since $\delta_{ij} \perp \beta_i$, variation in the discount + parametric assumption $\rightarrow$ identify the switching cost.
Define a new variable \( \tilde{U}_{ij(k)} := U_{ij} - \beta_i 1\{k_j \neq k(i, t - 1)\} \).

Same identification strategy as before identifies the distribution of \( U \), i.e., \( F_{\tilde{U}}(\cdot|X, Z) \).

Let \( F_\beta(\cdot|X) = F_\beta(\cdot|X; \gamma_\beta) \), finite unknown parameters \( \gamma_\beta \).

Objective: identify \( F_U(\cdot|X, Z) \) and \( F_\beta(\cdot; \gamma_\beta) \) from \( F_{\tilde{U}}(\cdot|X, Z) \).
We make the function form assumption:

\[ \beta_i = \beta_0 + \alpha X_i + \sigma^2(X) \nu_i, \quad \nu \perp X, \nu_i \sim N(0, 1), \]

Using cross-sectional data, we can estimate the discount insurers offer for new customers, so treat it a known.

Simplifying and using \( \mathbb{E}(\beta|X) = \beta_0 + \alpha X \) we get

\[
S_j(P, X, Z) = \frac{\exp(-U_{ij} - P_j - (\beta_0 + \alpha X - \hat{\delta}(k) - \hat{\gamma} X)1\{k_j \neq k(i, t - 1)})}{\sum_{j' = 0}^{J} \exp(-U_{ij'} - P_j - (\beta_0 + \alpha X - \hat{\delta}(k) - \hat{\gamma} X)1\{k_{j'} \neq k(i, t - 1)})},
\]

which, up to the parameters \((\beta_0, \xi)\) is same as model without switching cost.

But we can use the switchers \(1\{k_j \neq k(i, t - 1)\}\) to identify \(\beta_0\) and \(\xi\) as desired by following these two steps:

1. (1) As before (i.e., without switching cost) identify \(F_U(\cdot|X, Z)\);
2. (2) there is a unique \((\beta_0, \alpha)\) that equates shares of \(j\) observed in the data and the share predicted by the model.
usually when we estimate demand we know ex-ante the price of bundles

here we do not: hard to get price of each clause for nearly 50 companies + prices \( \neq \) tariff

as in any non-linear pricing problem prices differ across consumers \( \rightarrow \) the base premium depends on the driving record

we reconstruct the choice set by estimating hedonic premium functions \( \rightarrow \) predict the set of available policies

estimating precisely hedonic premium function is crucial for our exercise
Hedonic Price Regressions

- Consider the following hedonic price regression:

\[ p_{ijt} = c_j + \beta_0 X_{i,t}^{ind} + \beta_1 X_{i,t}^{car} + \beta_2 X_{i,t}^{clause} + \eta_i + \epsilon_{i,t} \]

we have the following clauses

- black box
- driving clauses
- protected bonus
- preliminary inspection
- repairing clause
- decreasing/increasing clauses \( \rightarrow \) controls for omitted clause
- coverage: max amount of damage at fault covered
we estimate the company-specific premium function by FE

CARA only relative price matter to choose a policy

CARA is consistent with FE estimator → no need to identify coefficients that are not company-specific as only shift the “base” premium
Some Results

Switching

- Using the specification in Cosconati (2016) → switching ⇒ premium cut of about 48 euros (about 10% on the premium)
- Decrease in the premium is about 7% if the driver has one accident on the record
- Younger switchers enjoy smaller premium cuts
- → Switching costs exist
Cosconati (2016)

1. poor driving record impact premia: driving record indicators have a different coefficient → non-linear pricing
2. the slope differs across companies → heterogeneity of pricing strategies

let $\Delta_j(\text{class1})$ and $\Delta_j(\text{AR1})$ be the increase in the premium at company $j$ if the driver goes from rating class 1 to class 2: the marginal cost of being in bonus-malus class 1
Sources of Sorting
Premium-Accident Schedule

- $\Delta j(\text{class}1)$ vary substantially in the market
Sources of Sorting
Premium-Accident Schedule

\[ \Delta_j(AR1) \] vary substantially in the market

Marginal Cost of Zero Accidents on the AR
Sources of Sorting and Identifying Variations in the Data

- heterogeneity of pricing is likely to generate sorting
- no dynamics + MH $\rightarrow$ price-accident slope shifts risk-type utility
- variations on the supply side $\rightarrow$ identify the company-specific risk preferences
future work and conclusions

preliminary conclusions

1. given our data it is possible to “theoretically” non-parametrically identify the distribution of preferences for risk/switching cost
2. enough variability in the data to “practically” identify the distributions + indirect evidence of switching cost + self-selection into companies
3. not having access to accidents and damage not at fault is a severe limitation we are trying to overcome by making extra assumptions
4. counterfactual experiments to perform: eliminate switching cost, introduce mandatory discounts on some clause, introduce no-fault system
5. → assess impact on accidents and welfare

road ahead

1. extend and incorporate the supply side and endogenize the coverage options.
2. preliminary work

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For a vector of premium $\mathbf{P} := (P_1, \ldots, P_J) \cup 0$ the probability that consumers with type $(T, \alpha)$ chooses coverage $j$ is

$$S_{ij}(\mathcal{U}, \mathbf{P}) = \frac{\exp(-P_j - U_{ij})}{\sum_{j'=0}^{J} \exp(-P_{j'} + U_{ij'})}$$

Unconditional probability of choosing $j$ is a mixture

$$S_j(\mathbf{P}) = \int_{t}^{\bar{t}} S_{ij}(\mathcal{U}, \mathbf{P})dF_{\mathcal{U}}(\mathcal{U}|X, Z, \xi_j).$$
Insurer $k$ sells $J_k$ coverages with specific load factor:

$$C^k = (C^k_1, \ldots, C^k_{J_k}) \in \mathbb{R}^{J_k}.$$  

Define $\Sigma_{jk} := \{ (\theta, a) : u_{ijk}(\theta, a) \geq u_{ij'k}(\theta, a), \forall j' \in J_k \}$. 

Risk pool $j$ policy: $\mathbb{E}(\theta|\Sigma_{jk})$. 

Insurance $k$ solves:

$$\max_{\{P_j\}_{j \in J_k}} \left\{ \mathbb{E}_\pi_k = \sum_{j \in J_k} S_j(P_k, P_{-k}) \left( P_j - \mathbb{E}(\theta|\Sigma_{jk}(P_k, P_{-k})) C^k_j \right) \right\}.$$  

s.t., IC and IR constraints.
Bunching

Figure: Consumer Type Space for four options.
Model

- FOCs at \((P_k, P_{-k}) = (P^*_k, P^*_{-k})\): for all \(j \in J_k\)
  \[
  D_j \mathbb{E}_{\pi_k} = \frac{\partial S_j}{\partial P_j} \left( P_j - \mathbb{E}(\theta|\Sigma_{jk}) C^k_j \right) + S_j \left( 1 - \frac{\partial\mathbb{E}(\theta|\Sigma_{jk})}{\partial P_j} C^k_j \right) \\
  + \sum_{j' \in J_k, j' \neq j} \left\{ \frac{\partial S_{j'k}}{\partial P_j} \left( P_{j'} - \mathbb{E}(\theta|\Sigma_{j'k}) C^k_{j'} \right) - S_{j'k} \frac{\partial\mathbb{E}(\theta|\Sigma_{j'k})}{\partial P_j} C^k_{j'} \right\} = 0.
  
- We assume that \(\{F(\theta, a), H(\cdot), F_\alpha\}\) are such that:
  1. For all \(j \in J, S_j\) is continuously differentiable in premiums.
  2. The type distribution \(F_T(\cdot|X, Z, \xi)\) is log-concave.

- If \(u(x; \theta)\) is quasi-concave in \(x\), and if \(\theta \sim F\) is log-concave
  then \(\int u(x; \theta) dF(\theta)\) is also quasi-concave.