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 **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 **identification**: given data on contracts and claims can we **identify** the parameters of interest?
- In this paper we focus on **demand** $\Rightarrow$ we keep supply as given $\Rightarrow$ 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 (θ) and risk preference (a).
   - Insurance companies only know $(\theta, a) \sim F(\cdot|X, Z)$.
   - (θ, 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?

Literature

- Asymmetric information $\rightarrow$ market failure $\rightarrow$ welfare loss.
- Rothschild and Stiglitz (1976) $\rightarrow$ severe adverse selection.
- Chiappori & Saline (2000): $corr(coverage, claim) \approx 0$.
- Found no evidence of adverse selection in French data.
- Recent papers: at best mixed evidence of adverse selection.
- Why? Theory is silent $\rightarrow$ truly an empirical question.

Literature

New "data-driven" approach

- Heterogenity in risk-preference + $corr(\theta, a) < 0 \rightarrow$ good drivers buy high coverage $\rightarrow corr(coverage, claim) \approx 0$.
- Private information **must be** multidimensional.
- Finkelstein & McGary (2006), Cohen & Einav (2006)
- And recently: Aryal, Perrigne & Vuong (2016).

Literature

- 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 $F(\cdot, \cdot|X, Z; \texttt{market})$ vary across market?
  2. What fraction of dispersion in premium across regions can be explained by differences in $F(\cdot, \cdot|X, Z; \texttt{market})$?
- Empirical: virtually none except Cosconati (2016)

Identifying Preferences for Risk: Issues

- Cohen and Einav (AER 2006) $\rightarrow$ risk aversion is more important than risk in determining demand for insurance
- $\rightarrow$ 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 $\Rightarrow$ **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

Selection into Companies and Preferences for Risk

- Cosconati (2016) $\rightarrow$ 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 $\rightarrow$ potential source of sorting
  - company dummies are significant in the accident probability $\rightarrow$ reduced form evidence of self-selection
- companies differ in terms of the clauses offered $\rightarrow$ 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.
  2. Estimation: closer to discrete choice model with multi-product oligopoly with asymmetric information.
  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.

Introduction to IPER

New Large Adimistrative Data on the Auto Insurance Market

- 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

- 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 $\Rightarrow$ 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 $\rightarrow$ we rationalize this by different loadings on Z across companies

Data on Claims

- 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.

- 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.

Model

Basic

- 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. $\Pr(\texttt{at least one accident}) = \theta$
  4. CARA utility: $v(w; a) = -\exp(-aw)$.
  5. Random damage: $D \sim H(\cdot|Z)$ over $[0, \overline{D}]$.
- Options: $J = \{1, 2, \ldots, J\}$ set of all options.
- Insurance contract:
  1. Premium-clauses pair $\{P_j, \xi_j\}$.
  2. Random indemnity: $\rightarrow E \sim \Psi(\cdot|\xi_j)$.
  3. All accidents in a year are “aggregated” into one.
- We consider demand without switching cost first.

$$
\begin{aligned}
\tilde{U}_{ij} &= (1-\theta_i)v(W_i - P_{ij}; a_i) \quad \texttt{no-accident} \\
&+\theta_i\lambda_j \int_0^{\overline{D}} v(W_i - P_{ij} - D; a_i)\mathrm{d}H(D|Z) \quad \texttt{at-fault} \\
&+\theta_i(1-\lambda_j)\int_0^{\overline{D}}\int_0^{D} v(W_i - P_{ij} - D + E; a_i)\mathrm{d}\Psi(E|\xi_j)\mathrm{d}H(D|Z) \\
&\qquad \texttt{not-at-fault} \\
CRRA &\rightarrow \tilde{U}_{ij} = -\exp(-a_i(W_i - P_j))\Bigg[1-\theta_i+\theta_i\Bigg(\lambda_j\mathbb{E}_H\big(\exp(a_iD)|Z\big) \\
&+(1-\lambda_j)\mathbb{E}_{\Psi,H}\big(\exp(-a_i(E-D))|X,Z;\xi_j\big)\Bigg)\Bigg] \\
\therefore \tilde{U}_{ij} &\equiv \exp(-a_i(W_i - P_j))\Bigg[1-\theta_i+\theta_i\Gamma(a_i;\lambda,H,\Psi,\xi_j)\Bigg].
\end{aligned}
$$

Model

- 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, ξ_j) is

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

- Solving for CE we get

$$\begin{aligned} CE(P_j, \xi_j; \theta_i, a_i) &= -P_j - \underbrace{\frac{1}{a_i} \ln \left[1 + \theta_i \left(\Gamma(a_i; \lambda, H, \Psi, \xi_j) - 1 \right) \right]}_{=\mathcal{U}_{ij}} \\ &\equiv -\mathcal{U}_{ij} - P_j. \end{aligned}$$

- One dimensional insuree type: $\mathcal{U}_{ij} \sim F_{\mathcal{U}}(\cdot | X, Z, \xi)$
- $\mathcal{U} \rightarrow$ one-dimensional sufficient statistic.

- Let the preferences be represented in terms of CE as

$$u_{ij} = CE_{ij} + \epsilon_{ij} = -\mathcal{U}_{ij} - P_{ij} + \epsilon_{ij}, \quad \epsilon_{ij} \sim T1EV \tag{1}$$

- Then, an insuree i chooses solves

$$j = \arg\max_{\tilde{j} \in J} u_{i\tilde{j}}.$$

- 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

$$S_j(P, X, Z) = \int_{\underline{u}}^{\overline{u}} S_{ij}(P, \mathcal{U}) \mathrm{d}F_{\mathcal{U}}(\mathcal{U}|X, Z). \tag{2}$$

Identification

- 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.

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

$$s_j = \int_{\mathcal{U}} \underbrace{k(p)}_{\texttt{known}} \underbrace{f_{\mathcal{U}}(u|x,z)}_{\texttt{unknown}} du$$

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 λ using Logit assumption + "at-fault" data.
5. Still figuring out how to identify $H(\cdot|Z)$ and the distribution of indemnity $(D - E)$

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

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

- Integrating this over the entire population gives

$$\begin{aligned}
\tilde{S}_j(P,X,Z) &= \int_{\underline{u}}^{\overline{u}} \tilde{S}_{ij}(P,\mathcal{U}) \mathrm{d}F_{\mathcal{U}}(\mathcal{U}_{ij}|X,Z) \\
&= \int_{\underline{u}}^{\overline{u}} \exp(-(P_j + \tilde{U}_0) - \mathcal{U}_{ij}) \mathrm{d}F_{\mathcal{U}}(\mathcal{U}_{ij}|X,Z) \\
&= \int_{\underline{u}}^{\overline{u}} \exp(-\tilde{P}_j - \mathcal{U}_{ij}) \mathrm{d}F_{\mathcal{U}}(\mathcal{U}_{ij}|X,Z).
\end{aligned}$$

- Convolution theorem $\rightarrow$ Laplace transform of $\tilde{S}$ is the product of the Laplace transform of $\exp(-\tilde{P}_j - \mathcal{U}_{ij})$ and $f_{\mathcal{U}}(\cdot|\cdot)$.
- Using $\mathcal{L}$ to denote the Laplace transform (suppress (X,Z)):

$$\mathcal{L}_{\tilde{S}}(u) = \mathcal{L}_{\exp}(u) \times \mathcal{L}_{f_{\mathcal{U}}}(u) \Rightarrow \mathcal{L}_{f_{\mathcal{U}}}(u) = \frac{\mathcal{L}_{\tilde{S}}(u)}{\mathcal{L}_{\exp}(u)}.$$

- Now, invert the Laplace to get

$$f_{\mathcal{U}}(u) = \frac{1}{2\pi\mathbf{i}} \lim_{T\to 0} \int_{-\mathbf{iT}}^{\mathbf{i}T} \exp(\xi u) \frac{\mathcal{L}_{\tilde{S}}(\xi)}{\mathcal{L}_{\exp}(\xi)} d\xi.$$

- There is a one to one mapping between (θ, a) and $(\mathcal{U}, a)$

$$\begin{pmatrix} \mathcal{U} \\ a \end{pmatrix} \longmapsto \begin{pmatrix} g_1(\mathcal{U}, a) = \theta \\ g_2(\mathcal{U}, a) = a \end{pmatrix}; \qquad g_1(\mathcal{U}, a) = \frac{\exp(a\mathcal{U}) - 1}{\Gamma(a_i; \lambda, H, \Psi, \xi) - 1}.$$

- Let J is the Jacobian of $g_1(\mathcal{U}, a)$. Then

$$\begin{aligned} f_{\mathcal{U},a}(\mathcal{U}(\theta, a), a) \times |J| &= f_{\theta,a}(\theta, a|X, Z) \\ &= f_{a|\theta}(a|\theta, X, Z) \times f_\theta(\theta|X, Z) \end{aligned}$$

- 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

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

- Thus

$$\begin{aligned} \Pr(A_i = 0) &= (1-\theta_i) + \theta_i(1-\pi_i)^{n_i}; \\ \Pr(A_i = \ell) &= \theta_i \binom{n_i}{\ell} \pi_i^{n_i}(1-\pi_i)^{n_i-\ell}, \ell = 1,2, n_i = 3. \end{aligned}$$

- Furthermore, let θ_i and π_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:

$$\begin{aligned}\log L &= \sum_{i=1}^{N} \Bigg\{ \mathbf{1}(A_i = 0) \log[e^{\tilde{X}_i\tau} + (1 + e^{\tilde{Z}_i\beta})^{-n_i}] - \log(1 + e^{\tilde{X}_i\tau}) \\ &\quad + (1 - \mathbf{1}(A_i = 0)) \times [a_i\tilde{Z}_i\beta - n_i \log(1 + e^{\tilde{Z}_i\beta}) + \log \binom{n_i}{a_i}] \Bigg\}.\end{aligned}$$

- 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 ω_i then the log-likelihood can be simplified to be

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

- Since ω_i is unknown, we can use Nested-Fixed Point algogrithm (or EM algorithm) to estimate conditional mean of ω_i given (β, τ).

- 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

$$\begin{aligned} & \prod_{i=1}^{2M} \Pr(Y=y_i|X=x_i, Z=z_i, \xi=\xi_i) \\ = & \prod_{i=1}^{2M} \Pr(Y=y_i|X=x_i, Z=z_i, \xi_i=\xi_j) \\ = & \prod_{i=1}^{2M} p(x_i, z_i, \xi_i; \kappa)^{y_i}(1-p(x_i, z_i, \xi_i; \kappa))^{1-y_i}. \end{aligned}$$

Let $\log(\frac{p}{1-p}) = e^{\kappa_0+\kappa_1 X+\kappa_2 Z+\kappa_3\xi}$, so

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

$$= \sum_{i=1}^{2M} -\log(1+e^{\kappa_0+\kappa_1 X+\kappa_2 Z+\kappa_3\xi}) + \sum_{i=1}^{2M} y_i(\kappa_0+\kappa_1 X+\kappa_2 Z+\kappa_3\xi).$$

Since

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

so identifying the indemnity distribution $\Psi(\cdot|\xi)$ and the damage distribution $H(\cdot|Z)$ is sufficient.

Demand with Switching Cost

- 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:

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

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

$$S_{ij} = \frac{\exp(-\mathcal{U}_{ij} - P_j - (\beta_i - \delta_{ij(k)})\mathbf{1}\{k_j \neq k(i,t-1)\})}{\sum_{j'=0}^{J} \exp(-\mathcal{U}_{ij'} - P_j - (\beta_i - \delta_{ij'(k)})\mathbf{1}\{k_{j'} \neq k(i,t-1))}.$$

Identification
$F_\beta(\cdot)$

- 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

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

- 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 $\tilde{\mathcal{U}}_{ij(k)} := \mathcal{U}_{ij} - \beta_i \mathbf{1}\{k_j \neq k(i, t-1)\}$.
- Same identification strategy as before identifies the distribution of $\mathcal{U}$, i.e., $F_{\tilde{\mathcal{U}}}(\cdot|X, Z)$.
- Let $F_\beta(\cdot|X) = F_\beta(\cdot|X; \gamma_\beta)$, finite unknown parameters γ_β.
- Objective: identify $F_{\mathcal{U}}(\cdot|X, Z)$ and $F_\beta(\cdot; \gamma_\beta)$ from $F_{\tilde{\mathcal{U}}}(\cdot|X, Z)$.

- We make the function form assumption:

$$\beta_i = \beta_0 + \alpha X_i + \sigma^2(X)\nu_i, \quad \nu \perp X, \nu_i \sim \mathcal{N}(0,1),$$

- 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

$$s_j(P,X,Z) = \frac{\exp(-\mathcal{U}_{ij} - P_j - (\beta_0 + \alpha X - \hat{\delta}_{j(k)} - \hat{\gamma}X)\mathbf{1}\{k_j \neq k(i,t-1)\})}{\sum_{j'=0}^{J} \exp(-\mathcal{U}_{ij'} - P_j - (\beta_0 + \alpha X - \hat{\delta}_{j'(k)} - \hat{\gamma}X)\mathbf{1}\{k_{j'} \neq k(i,t-1))},$$

 which, up to the parameters (β_0, ξ) is same as model without switching cost.
- But we can use the switchers $\mathbf{1}\{k_j \neq k(i,t-1)\})$ to identify β_0 and ξ as desired by following these two steps:
  1. (1) As before (i.e., without switching cost) identify $F_{\mathcal{U}}(\cdot|X,Z)$;
  2. (2) there is a unique (β_0, α) that equates shares of j observed in the data and the share predicted by the model.

Choice Sets

- 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:

$$p_{ijt} = c_j + \beta_0 X^{ind}_{i,t} + \beta_1 X^{car}_{i,t} + \beta_{2,j} X^{clause}_{i,t} + \eta_i + \epsilon_{i,t}$$

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

Hedonic Premium Regressions

- we estimate the company-specific premium function by FE
- CARA only relative price matter to choose a policy
- CARA is consistent with FE estimator $\rightarrow$ no need to identify coefficients that are not company-specific as only shift the "base" premium

Some Results

Switching

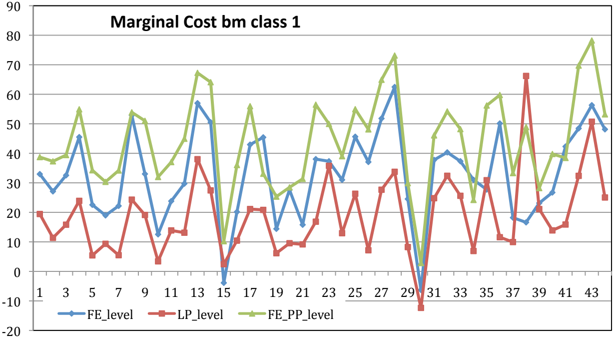
- Using the specification in Cosconati(2016) $\rightarrow$ switching $\Rightarrow$ premium cut of about 48 euros (about 10% on the premium)
- decrease in the premium is about 7% if the drivers has one accident on the record
- younger switcher enjoy smaller premium cuts
- $\rightarrow$ switching costs exists

Non-linear pricing in the market

- 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 $\Delta_j(class1)$ and $\Delta_j(AR1)$ 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

- $\Delta_j(class1)$ vary substantially in the market



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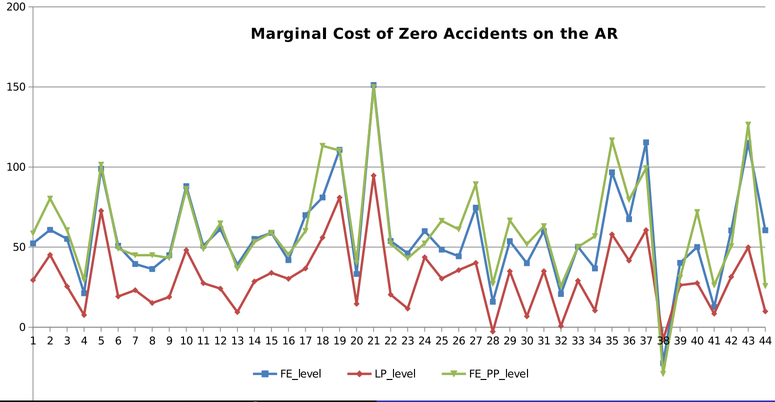
Sources of Sorting

Premium-Accident Schedule

- $\Delta_j(AR1)$ vary substantially in the market



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 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 Supply Side

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

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

- Unconditional probability of choosing j is a mixture

$$S_j(\mathbf{P}) = \int_{\underline{t}}^{\overline{t}} S_{ij}(\mathcal{U}, \mathbf{P}) \mathrm{d}F_{\mathcal{U}}(\mathcal{U}|X, Z, \xi_j).$$

Model

- Insurer k sells J_k coverages with specific load factor: $\mathbf{C}^k = (C_1^k, \ldots, C_{J_k}^k) \in \mathbb{R}_+^{|J_k|}$.
- Define $\Sigma_{jk} := \left\{(\theta, a) : \quad u_{ijk}(\theta, a) \geq u_{ij'k}(\theta, a), \forall j' \in J_k\right\}$.
- Risk pool j policy: $\mathbb{E}(\theta|\Sigma_{jk})$.
- Insurance k solves:

$$\max_{\{P_j\}_{j\in J_k}} \left\{\mathbb{E}\pi_k \quad = \quad \sum_{j\in J_k} S_j(\mathbf{P}_k, \mathbf{P}_{-k}) \left(P_j - \mathbb{E}(\theta|\Sigma_{jk}(\mathbf{P}_k, \mathbf{P}_{-k}))C_j^k\right)\right\}.$$

s.t., IC and IR constraints.

Bunching

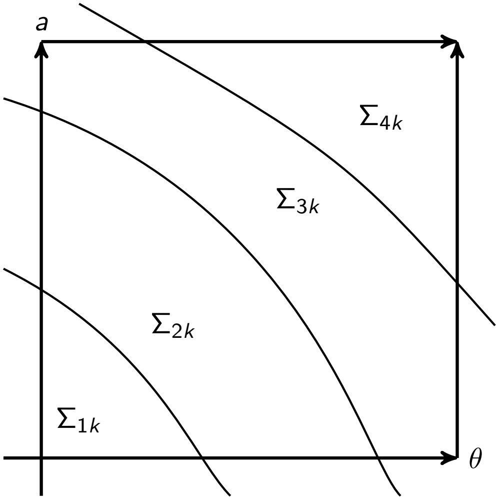


Figure: Consumer Type Space for four options.

Model

- FOCs at $(\mathbf{P}_k, \mathbf{P}_{-k}) = (\mathbf{P}^*_k, \mathbf{P}^*_{-k})$: 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 $\int u(x;\theta)\mathrm{d}F(\theta)$ is also quasi-concave.
- Flinn and Heckman (1983); Caplin and Nalebuff (1991).