Competing under Information Heterogeneity: Evidence from Auto Insurance

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July 8, 2025

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Motivation

- Firms increasingly differ in *information precision* (data access/analytics) and in *cost structures*.
- This creates information asymmetries *between* firms (beyond classic buyer–seller asymmetry).
- Policy interest: regulations that equalize or share consumer risk information (e.g., centralized "risk bureau", Open Banking policies).

This paper

- Research Questions
  - How does heterogeneous information across insurers shape market equilibrium?
  - What are the equilibrium impacts of establishing a centralized bureau to equalize information access?
- Contributions
  - A tractable model of imperfect competition with firm-specific information precision and costs.
  - New identification/estimation strategy using offered-price distributions and demand to recover signals.
  - Evidence from Italian auto liability insurance with rich panel linking consumers across insurers.
  - Counterfactuals: centralized risk bureau, full information, and privacy/high-variance restrictions.

Literature

1. Selection markets
   - Competitive models: Einav et al. (2010, 2011), Azevedo & Gottlieb (2017); Assymmetric information: Cabral et al. (2018), Crawford et al. (2018), Cuesta et al. (2021) and Tebaldi (2024)
     $\rightarrow$ Incorporates multidimensional cost heterogeneity
2. Demand estimation
   - Berry (1994), BLP(1995) and D'Haultfœuille et al. (2019)
     $\rightarrow$ Extends demand estimation when prices are not observed.
3. Antitrus/Consumer protection and Big Data
   - Einav et al. (2013), Chatterjee et al. (2023), Blattner & Nelson (2021), Lam & Liu (2020), Jin & Wagman (2021)
     $\rightarrow$ Policies that equalize information access can improve competition

Outline

Setting and Data

Descriptive evidence

Model

Estimation

Results and Counterfactuals

Appendix

Institutional Background: Italian Auto Liability (RCA)

- Mandatory, annual, exclusive contracts; insurers cannot reject consumers.
- Large market: $\approx$31M contracts in 2018; $\approx$50 national competitors.
- Key contract features widely standardized; little use of deductibles.

Data: IVASS IPER Microdata

- Nationally representative matched insurer–insuree panel with claims frequency/severity, premiums, coverage.
- Tracks policyholders across insurers and time $\Rightarrow$ measure risk using ex-post claims panel.
- Focus sample: new customers in Rome (2013–2021); top 10 firms + fringe group.

Outline

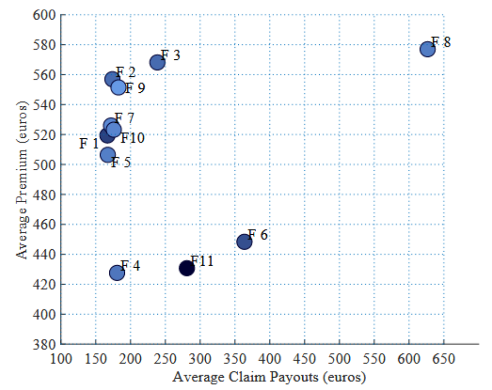
Sample & Summary Statistics

- $N \approx$ 124,428 contracts; avg premium $\approx$ 478; within-year claim rate $\approx$ 0.08.
- Demographics/vehicle: 56% male; avg age 48; BM class $\approx$ 2; car age $\approx$ 8.3 years.

Table 1: Summary statistics

Variables	Mean	Std. Dev.	Min	Max	N
Premium (€)	477.68	208.79	133.68	1335.05	124,428
Claim size (€)	260.89	10217.58	0	2521014	124,428
No. of claims (within contract year)	0.08	0.29	0	4	124,428
No. of accidents in last 5 years	0.81	1.22	0	3	124,428
BM class	2.06	2.51	1	15	124,428
Age	48.24	14.11	18	99	124,428
Man	0.56	0.50	0	1	124,428
Median city	0.10	0.30	0	1	124,428
Big city	0.62	0.49	0	1	124,428
Car age	8.30	5.27	0	19	124,428
Horsepower	66.88	26.84	0	493	124,428
Petrol vehicle	0.52	0.50	0	1	124,428
One installment	0.67	0.47	0	1	124,428

Stylized Facts: Price Variation & Sorting



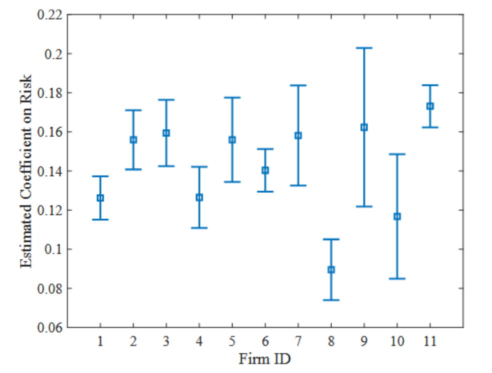
- Large cross-firm variation in average premiums even at similar average risks/market shares.
- Firms with higher average claim costs attract riskier consumers ⇒ sorting across firms.

Measuring Information Precision

1. Step 1: Construct individual risk measures
   - Panel regression of claim counts and size with individual fixed effects
   - Risk measure $= \underbrace{\exp(X_{it}\delta_c + \zeta_i)}_{\text{Claim Count}} \cdot \underbrace{\exp(\delta_0 + X_{it} + \eta_{it})}_{\text{Claim Size}}$
2. Step 2: Firm-specific premium-risk regressions
   - For each firm j: $\text{Premium}_{ij} = \alpha_j + \beta_j \cdot \text{Risk}_i + \varepsilon_{ij}$
   - Higher β_j suggests firm's prices are more responsive to actual risk

Heterogeneity in Risk Sensitivity

- Strong cross-firm differences in premium–risk slopes ⇒ heterogeneous precision?
- Prices are equilibrium outcomes ⇒ need structural model to recover information precision.



Outline

Model overview

- J insurers; standardized product; no outside option.
- Consumer true risk θ (expected cost/year) unobserved ex ante.
- Firm j observes a private signal $\hat{\theta}_j$ with precision that differs across firms.
- D denotes the contract chosen by the consumer.

Signal Structure

$$\hat{\theta}_j \sim \mathcal{N}(\theta,\ \sigma_j^2), \quad \text{iid} \tag{1}$$

- Denote by $\phi(\hat{\theta}_j \mid \theta, \sigma_j)$ the density
- Lower $\sigma_j^2 \Rightarrow$ higher information precision for firm j.
- Signals are used to form posterior beliefs about θ *conditional on selection*.

$$E(\theta|\hat{\theta}_j, D=j) = \int_\theta \theta f(\theta|\hat{\theta}_j, D=j) d\theta = \frac{\int_\theta \theta \overbrace{\Pr(D=j|\hat{\theta}_j,\theta)}^{\text{Selection Prob.}} \phi(\hat{\theta}_j;\theta,\sigma_j) f_0(\theta) d\theta}{\int_\theta \Pr(D=j|\hat{\theta}_j,\theta)\phi(\hat{\theta}_j;\theta,\sigma_j) f_0(\theta) d\theta} \tag{2}$$

Pricing

- Assumes:

$$p_j(\hat{\theta}_j) \;=\; \alpha_j \;+\; \beta_j \, \mathbb{E}[\theta \mid \hat{\theta}_j,\, D = j], \tag{3}$$

- α_j: baseline markup; β_j: sensitivity to risk rating.
- $\mathbb{E}[\theta \mid \hat{\theta}_j, D = j]$ embeds selection $\Rightarrow$ nonlinearity in $\hat{\theta}_j$.

Demand

- Consumers choose one insurer (no outside option); utility depends on price and observable characteristics.
- Preference parameters allowed to vary with observables and risk type. Consumer i's utility from firm j:

$$U_{ij} = -\gamma(\theta)p_j(\tilde{\theta}_j) + \xi_j(\theta) + \varepsilon_{ij} \tag{4}$$

$$\Pr(D = j|\hat{\theta}, \theta) = \frac{\exp(-\gamma(\theta)p_j(\hat{\theta}_j) + \xi_j(\theta))}{\sum_{j'=1}^{J} \exp(-\gamma(\theta)p_{j'}(\hat{\theta}_{j'}) + \xi_{j'}(\theta))} \tag{5}$$

Firm profits

- Firms simultaneously choose pricing coefficients (α_j, β_j) to maximize expected profits, given common knowledge of all firms' primitives (e.g., signal distributions, costs) and $f_0(\theta)$.
- Firm j's profit

$$\pi_j(\alpha, \beta) = \int_{\hat{\theta}} \int_{\theta} \underbrace{(p_j(\hat{\theta}_j) + c_j - k_j\theta)}_{\text{net profit}} \underbrace{\Pr(D = j|\hat{\theta})}_{\text{choice prob.}} \underbrace{\left(\prod_{j'=1}^{J} \phi(\hat{\theta}_{j'}; \theta, \sigma_{j'}) \right)}_{\text{signal dist.}} \underbrace{f_0(\theta)}_{\text{type dist.}} \; d\theta d\hat{\theta}.$$

- c_j: "net benefits" of contracting with a customer irrespective of the risk.
- k_j: efficiency at processing claims.

Outline

Estimation Overview

- Joint distribution of premium and risk types ▸ Details
  - Uses panel of claim records
  - Claim size estimated via regression
  - Accident rate identified from panel of accident counts (repeated noisy measurements)
  - Output $\hat{g}(p|\theta, D = j)$
- Demand $(\gamma(\theta), \xi_j(\theta))$
  - $\xi_j(\theta)$: matched to observed market shares
  - $\gamma(\theta)$: identified from sorting patterns
- Supply $(\alpha_j, \beta_j, \sigma_j^2, c_j, k_j)$
  - Average price conditional on risk identifies (α_j, β_j) ▸ Details
  - σ_j is identified from price dispersion given risk ▸ Details
  - Cost parameters (c_j, k_j) recovered from first-order conditions ▸ Details

Demand Estimation

Challenge:

- Observe **accepted prices**, not offered prices
- Lower prices over-represented in data

Solution:

- Use selection rule (demand model) to recover distribution of offered prices

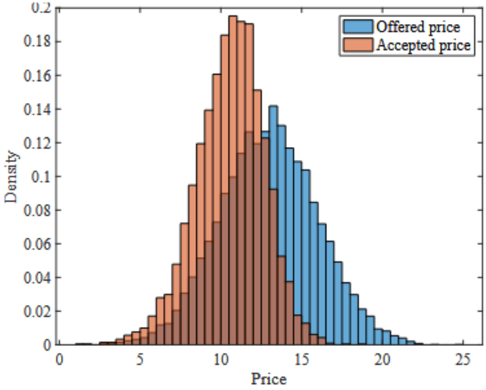
Relationship:

$$g(p|\theta, D = j) \propto g_j(p|\theta)\,\mathrm{Pr}(D = j|p_j = p, \theta)$$

Recover offered prices:

$$g_j(p|\theta) = \frac{g(p|\theta, D = j)/\,\mathrm{Pr}(D = j|p_j = p, \theta)}{\int_{p'} g(p|\theta, D = j)/\,\mathrm{Pr}(D = j|p_j = p', \theta)dp'}$$

▸ Details



(b) Density

Iterative Algorithm for Demand Estimation

Nested Fixed-Point Algorithm: Jointly estimate sorting probabilities, price distributions, and demand parameters

Inner Loop: For fixed γ (price sensitivity)

1. Initialize: $\xi_j^1 = 0$ and $\Pr^1(D = j | p_j = p, \theta) = \exp(\alpha p)$ for all j
2. Update offered-price density, using Bayes' rule:
$$g_j^r(p|\theta) = \frac{\hat{g}(p|\theta, D = j) / \Pr^r(D = j | p_j = p, \theta)}{\int_{p'} \hat{g}(p'|\theta, D = j) / \Pr^r(D = j | p_j = p', \theta) dp'}$$
3. Update ξ^{r+1} to match observed market shares:
$$\hat{s}_j = \int_\theta \int_p \frac{\exp(\alpha p_j + \xi_j^{r+1})}{\sum_{j'} \exp(\alpha p_{j'} + \xi_{j'}^{r+1})} \left(\prod_{j'} g_{j'}^r(p_{j'}|\theta) \right) f_0(\theta) dp d\theta$$
4. Update selection probabilities $\Pr^{r+1}(D = j | p_j = p, \theta)$ using demand model
5. Iterate until g^r converges. Output $\{g_j(p \mid \theta; \gamma)\}_j$, $\Pr(D = j \mid p, \theta; \gamma)$, and $\xi(\gamma)$.

Outer Loop: Estimate α by matching risk sorting patterns via maximum likelihood

Outline

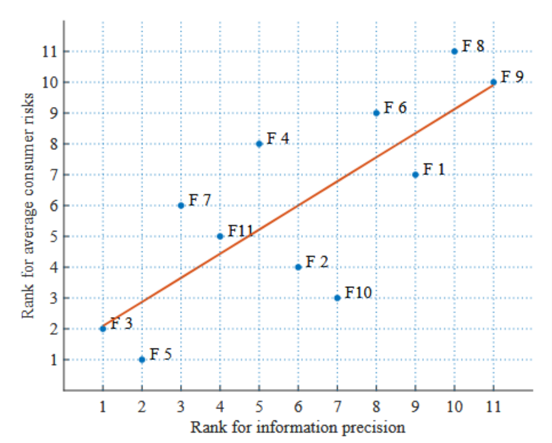
Results: Supply-Side

- Large differences in information precision (σ_j^2) and price sensitivity (β_j) across firms
- Baseline markups (α_j) differ, consistent with market power from information advantages
- Large contracting net benefits (e.g., for F8 is four times average premium)
- Heterogeneity in claim efficiency(e.g. F8 roughly 2.5 times less efficient than F6)

Table 3: Estimates of supply-side parameters

Firm ID	Pricing Coefficients		Signal Std. Dev.	Net Benefits	Claim Efficiency
	α_j	β_j	σ_j	c_j	k_j
1	-342.22	1.72	1339.05	1165.31	1.90
	(48.56)	(0.10)	(56.12)	(346.43)	(0.34)
2	-333.44	1.81	1217.08	1087.50	1.98
	(80.47)	(0.17)	(83.71)	(349.50)	(0.37)
3	-163.18	1.65	1053.16	1110.60	2.29
	(43.31)	(0.10)	(72.66)	(280.35)	(0.26)
4	-315.64	1.45	1178.77	1034.33	1.60
	(58.59)	(0.12)	(72.82)	(237.37)	(0.20)
5	-194.72	1.65	1117.57	922.39	1.86
	(61.41)	(0.16)	(85.78)	(290.10)	(0.31)
6	-310.08	1.47	1301.49	943.08	1.37
	(43.47)	(0.09)	(60.30)	(273.87)	(0.24)
7	-220.93	1.50	1118.80	858.29	1.54
	(90.81)	(0.19)	(115.56)	(293.74)	(0.33)
8	-1404.66	3.00	1580.41	2132.07	3.16
	(252.91)	(0.39)	(119.79)	(371.91)	(0.49)
9	-688.85	2.15	1637.52	1440.84	2.45
	(312.62)	(0.57)	(172.54)	(424.11)	(0.74)
10	-246.68	1.59	1245.79	972.73	1.79
	(138.25)	(0.28)	(107.35)	(317.01)	(0.39)

- More(less) precise firms, attract less(more) risky consumers



Counterfactuals: Information Policies

- **Centralized Risk Bureau**: aggregate firms' signals (weighted by precision), share equally with all.

$$E(\theta|\hat{\theta}) = \int_\theta \theta f(\theta|\hat{\theta}) d\theta = \frac{\int_\theta \theta \left(\prod_j \phi(\hat{\theta}_j; \theta, \sigma_j) \right) f_0(\theta) d\theta}{\int_\theta \left(\prod_j \phi(\hat{\theta}_j; \theta, \sigma_j) \right) f_0(\theta) d\theta} \tag{6}$$

- **Full Information Benchmark**: firms observe true θ (eliminate information asymmetry).
- **Privacy/Restriction**: firms can only use basic information; set σ_j^2 to the worst observed.

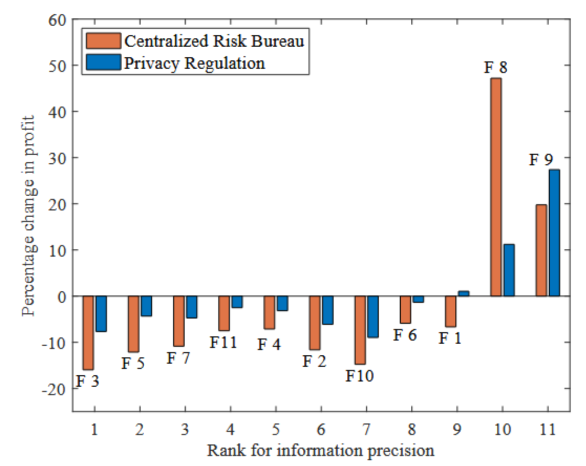
Counterfactuals: results

- Eliminating information asymmetries helps consumers.
- More(less) info. benefits less(more) risky consumers, due to less(more) cross-subsidies.

	Baseline	Observing True Risk	Centralized Risk Bureau	Privacy Regulation
Average CS (€)	-542.83	-451.05 (+16.91%)	-457.59 (+15.70%)	-523.42 (+3.57%)
Average CS: Low risk (€)	-477.24	153.74 (+132.21)	-103.63 (+78.28%)	-480.25 (-0.63%)
Average CS: High risk (€)	-608.42	-1055.83 (-73.54%)	-811.55 (-33.39%)	-566.60 (+6.87%)
Average premium (€)	461.25	342.56 (-25.73%)	361.61 (-21.60%)	441.79 (-4.22%)
Average profit (€)	849.58	802.11 (-5.59%)	799.29 (-5.92%)	834.38 (-1.79%)
HHI	2297.26	2241.40	2264.29	2303.38

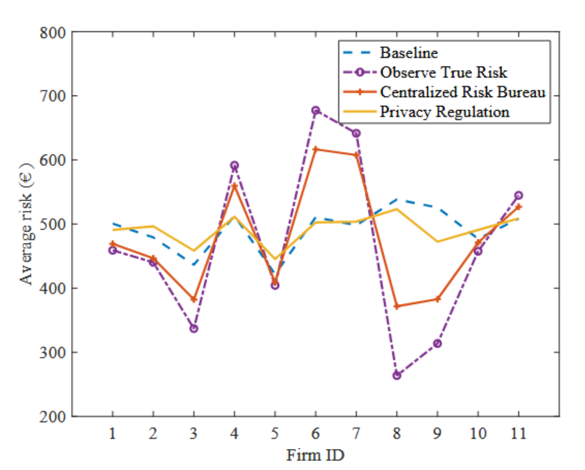
Change in firm profits

- Equalizing information weakens market power of precise firms.
- Common risk evaluation $\Rightarrow$ more effective undercutting $\Rightarrow$ stronger price competition.
- Perfect correlation in signals (uniform risk evaluation) leads to higher price competition.



Who goes where? Sorting patterns

- With equal access to risk, firms more efficient at processing claims re-target higher-risk consumers.
- Sorting shifts from info advantages (baseline) to cost specialization (bureau).
  $\rightarrow$ increases efficiency, avg cost $\downarrow$ by $\sim$3.7%
- Sorting is lowest under privacy regulation.



Conclusion

- This paper develops empirical framework for studying competition under information assymetries
- This paper studies the impacts of a credit bureau, it finds:
    - Centralized information can lower prices, raise consumer surplus and reorient sorting toward cost efficiency.
    - Distributional trade-offs: low-risk consumers gain more under information sharing; high-risk under privacy.
    - Industry composition effects: advanced-screening firms lose profits; potential dynamic innovation effects.

Comments

- What is the impact of a credit bureau on a dynamic world with learning-switching costs?
  - Cost of risk missclassification is low -> can update prices.
  - c_j should be risk specific to capture inertia?
- What is a credit bureau doing in the model
  - Pooling Data: if there are economies of scale, what is the market failure?
  - Sharing algorithms: impact of investment in algorithms.

Outline

Identification of Risk Types

- Risk type $\theta_i = \underbrace{\mu}_{\text{claim size}} \underbrace{\lambda_i}_{\text{accident rate}}$,
- Claim size μ estimated via regression
- Accident rate λ_i (latent variable) identified from panel of accident counts (repeated noisy measurements)
- Observe accident counts y_{it} over T periods: $y_{it} \sim \text{Poisson}(\lambda_i)$
- Joint distribution of counts identifies $f(\lambda_i | p_i, D_i = j)$:

$$f(y_{i1}, y_{i2}, \ldots, y_{iT} | p_i, D_i = j) = \int \prod_{t=1}^{T} \frac{\lambda_i^{y_{it}} e^{-\lambda_i}}{y_{it}!} f(\lambda_i | p_i, D_i = j) d\lambda_i$$

- Output $\hat{g}(p | \theta, D = j)$ for demand estimation Go back

Conditional choice probabilities

- Demand is produced by the model:

$$\Pr(D = j | p_j = p, \theta) = \int_{\mathbf{p}_{-j}} \frac{\exp(-\gamma p + \xi_j)}{\exp(-\gamma p + \xi_j) + \sum_{j' \neq j} \exp(-\gamma p_{j'} + \xi_{j'})} \left(\prod_{j' \neq j} g_{j'}(p'_{j'} | \theta) \right) d\mathbf{p}_{-j}.$$

Go back

Identification of Pricing Coefficients (α_j, β_j)

- Pricing strategy: $p_j(\hat{\theta}_j) = \alpha_j + \beta_j E(\theta|\hat{\theta}_j, D = j)$
- **Key Insight:** Linear structure allows identification from first and second moments
- **Objects already recovered:** within-firm offered-price density $g_j(p \mid \theta)$

Within-firm moments:

$$\text{Mean premium:} \quad E(p|D=j) = \alpha_j + \beta_j E(E(\theta|\hat{\theta}_j, D=j)|D=j) = \alpha_j + \beta_j E(\theta|D=j)$$

$$\text{Premium and Risk covariance:} \quad \text{cov}(p, \theta|D=j) = \beta_j \text{var}(E(\theta|\hat{\theta}_j, D=j)|D=j) = \frac{\text{var}(p|D=j)}{\beta_j}$$

Solution: Solve system of two linear equations

$$\beta_j \;=\; \frac{\text{var}(p \mid D=j)}{\text{cov}(p, \theta \mid D=j)}, \qquad \alpha_j \;=\; \mathbb{E}(p \mid D=j) \;-\; \beta_j\, \mathbb{E}(\theta \mid D=j),$$

Advantage: estimated separately from other parameters $\rightarrow$ reduces computational burden Go back

Identification of Signal Variance (σ_j)

- **Key Insight:** monotonicity of prices on the signal (similar to GPV(2000))

1. Using monotonicity and then inverting:

$$G_j(p_j(\hat{\theta}_j)|\theta) = \Phi\left(\frac{\hat{\theta}_j - \theta}{\sigma_j}\right) \implies p_j^o(\hat{\theta}_j; \theta, \sigma_j) = G_j^{-1}\left(\Phi\left(\frac{\hat{\theta}_j - \theta}{\sigma_j}\right)\right)$$

   where $G_j(p|\theta)$ = CDF of offered prices (recovered from demand estimation)

2. For a given σ_j, evaluate risk rating at equilibrium prices:

$$E(\theta|\hat{\theta}_j, D = j; \sigma_j) = \frac{\int_\theta \theta \Pr(D = j|p_j^o(\hat{\theta}_j; \theta, \sigma_j), \theta)\phi(\hat{\theta}_j; \theta, \sigma_j) f_0(\theta) d\theta}{\int_\theta \Pr(D = j|p_j^o(\hat{\theta}_j; \theta, \sigma_j), \theta)\phi(\hat{\theta}_j; \theta, \sigma_j) f_0(\theta) d\theta}$$

3. Using $p_j(\hat{\theta}_j; \sigma_j) = \hat{\alpha}_j + \hat{\beta}_j E(\theta|\hat{\theta}_j, D = j; \sigma_j)$ obtain the model-implied joint distribution of (p, θ) within firm j
4. Match model implied dist. of (p, θ) to the empirical dist. recovered from the data.

Supply parameters: c_j, k_j

Net profit from servicing consumer: $p_j(\hat{\theta}_j) + c_j - k_j\theta$

- c_j = net benefit from contracting (inertia, dynamic pricing, cross-selling)
- $k_j\theta$ = claim processing cost (efficiency parameter k_j times expected claims)

First-Order Conditions: Firm j optimally chooses (α_j, β_j)

$$\frac{\partial \pi_j}{\partial \alpha_j} = \int_\theta \int_{\hat{\theta}} \Pr(D = j \mid \hat{\theta}, \theta)\, f(\hat{\theta} \mid \theta) f_0(\theta)\, d\hat{\theta}\, d\theta + \int_\theta \int_{\hat{\theta}} (\alpha_j + \beta_j\theta + c_j - k_j\theta)\, \frac{\partial \Pr(D = j \mid \hat{\theta}, \theta)}{\partial \alpha_j}\, f(\hat{\theta} \mid \theta) f_0(\theta)\, d\hat{\theta}\, d\theta,$$

$$\frac{\partial \pi_j}{\partial \beta_j} = \int_\theta \int_{\hat{\theta}} \theta\, \Pr(D = j \mid \hat{\theta}, \theta)\, f(\hat{\theta} \mid \theta) f_0(\theta)\, d\hat{\theta}\, d\theta + \int_\theta \int_{\hat{\theta}} (\alpha_j + \beta_j\theta + c_j - k_j\theta)\, \frac{\partial \Pr(D = j \mid \hat{\theta}, \theta)}{\partial \beta_j}\, f(\hat{\theta} \mid \theta) f_0(\theta)\, d\hat{\theta}\, d\theta.$$

Solution: Given previously recovered $\{g_j,\ E(\theta \mid \hat{\theta}_j, D = j),\ \alpha_j,\ \beta_j,\ \sigma_j\}$ and $\Pr(D = j \mid \cdot)$, it is a system of 2 linear equations in (c_j, k_j) where all other terms are known ▸ Go back