Adverse Selection, Loss Coverage and Equilibrium Premium in Insurance Markets

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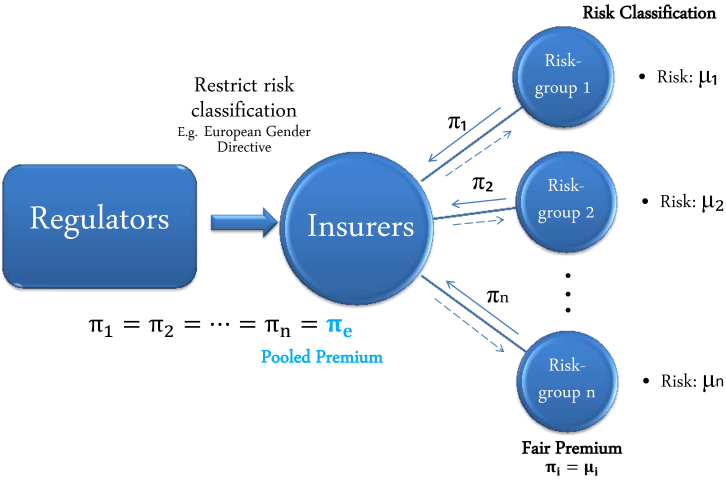
Background

How insurance works and risk classification scheme



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Adverse Selection

- $0, \pi_1, \pi_2, \pi_3, \pi_e, \ldots, \pi_7, \pi_8, \ldots, \pi_n, 1.$

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Original definition

Purchasing decision is positively correlated with losses
-Chiappori and Salanie (2000) "Positive Correlation Test"

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- Empirical results are mixed and vary by market.

Life Insurance	Cawley and Philipson (1999)	X
Auto Insurance	Chiappori and Salanie (2000)	X
	Cohen (2005)	O
Annuity	Finkelstein and Poterba (2004)	O
Health Insurance	Cardon and Hendel (2001)	X

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Definition

$$\text{Adverse Selection (AS)} = \frac{\text{expected claim per policy}}{\text{expected loss per risk}} = \frac{E[QL]}{E[Q]E[L]}, \qquad (1)$$

where Q: quantity of insurance; L: risk experience.

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$$\text{Adverse Selection Ratio: } S = \frac{\text{AS at pooled premium } \pi_e}{\text{AS at risk-differentiated premiums}}. \tag{2}$$

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S > 1 $\Rightarrow$ Adverse Selection.

Example

Example

- A population of 1000
- Two risk groups
  - 200 high risks with risk 0.04
  - 800 low risks with risk 0.01
- No moral hazard

Example

Full risk classification

Example

Full risk classification

	Low risks	High risks	Aggregate
Risk	0.01	0.04	0.016
Total population	800	200	1000
Expected population losses	8	8	16
Break-even premiums (**differentiated**)	0.01	0.04	0.016
Numbers insured	400	100	500
Adverse Selection Ratio (S)			1

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Restriction on risk classification-Case 1

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	Low risks	High risks	Aggregate
Risk	0.01	0.04	0.016
Total population	800	200	1000
Expected population losses	8	8	16
Break-even premiums (**pooled**)	0.02	0.02	0.02
Numbers insured	300(400)	150(100)	450(500)
Adverse Selection Ratio (S)			1.25>1

Example

Restriction on risk classification-Case 1

	Low risks	High risks	Aggregate
Risk	0.01	0.04	0.016
Total population	800	200	1000
Expected population losses	8	8	16
Break-even premiums (**pooled**)	0.02	0.02	0.02
Numbers insured	300(400)	150(100)	450(500)
Adverse Selection Ratio (S)			1.25>1

Moderate adverse selection

Example

Restriction on risk classification-Case 2

Example

Restriction on risk classification-Case 2

	Low risks	High risks	Aggregate
Risk	0.01	0.04	0.016
Total population	800	200	1000
Expected population losses	8	8	16
Break-even premiums (**pooled**)	0.02154	0.02154	0.02154
Numbers insured	200(400)	125(100)	325(500)
Adverse Selection Ratio (S)			1.3462>1

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	Low risks	High risks	Aggregate
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Heavier adverse selection

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Heavier adverse selection

Adverse selection suggests pooling is always bad. But is it?

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Loss Coverage

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- Thomas (2008, 2009) **"Loss Coverage"**:

Definition

$$\begin{aligned} \text{Loss Coverage (LC)} &= \frac{\text{insured expected losses}}{\text{population expected losses}} \\ \text{Loss Coverage Ratio: } C &= \frac{\text{LC at a pooled premium } \pi_e}{\text{LC at at risk-differentiated premium } \pi_i} \\ &> 1, \textbf{Favorable!} \end{aligned}$$

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Total population	800	200	1000
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Numbers insured	400	100	500
Insured losses	4	4	8
Loss coverage ratio (C)			1

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No restriction on risk classification

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Risk	0.01	0.04	0.016
Total population	800	200	1000
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Break-even premiums (**differentiated**)	0.01	0.04	0.016
Numbers insured	400	100	500
Insured losses	4	4	8
Loss coverage ratio (C)			1

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Numbers insured	300(400)	150(100)	450(500)
Insured losses	3	6	9
Loss coverage ratio (C)			1.125>1

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Numbers insured	300(400)	150(100)	450(500)
Insured losses	3	6	9
Loss coverage ratio (C)			1.125>1

Moderate adverse selection ($S = 1.25$**) but favorable loss coverage.**

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Heavier adverse selection ($S = 1.3462$) and worse loss coverage.

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Heavier adverse selection ($S = 1.3462$) and worse loss coverage.
Loss Coverage might be a better measure!

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Demand Function

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The demand function $d(\mu, \pi)$ is the demand of a single individual with risk μ, will buy insurance at premium π.

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- $\frac{\partial^2}{\partial \pi^2} d(\mu, \pi) > 0 \Rightarrow$ a decreasing rate of fall in demand as premium increases.

Definition

The demand elasticity $\epsilon(\mu, \pi) = -\frac{\partial d(\mu,\pi)}{d(\mu,\pi)} / \frac{\partial \pi}{\pi}$ i.e. sensitivity of demand to premium changes.

Demand Function

Iso-elastic demand function

$$
\begin{aligned}
d(\mu,\pi) &= \tau\left[\frac{\pi}{\mu}\right]^{-\lambda} \\
\epsilon(\mu,\pi) &= \lambda, \text{ i.e. constant}
\end{aligned}
$$

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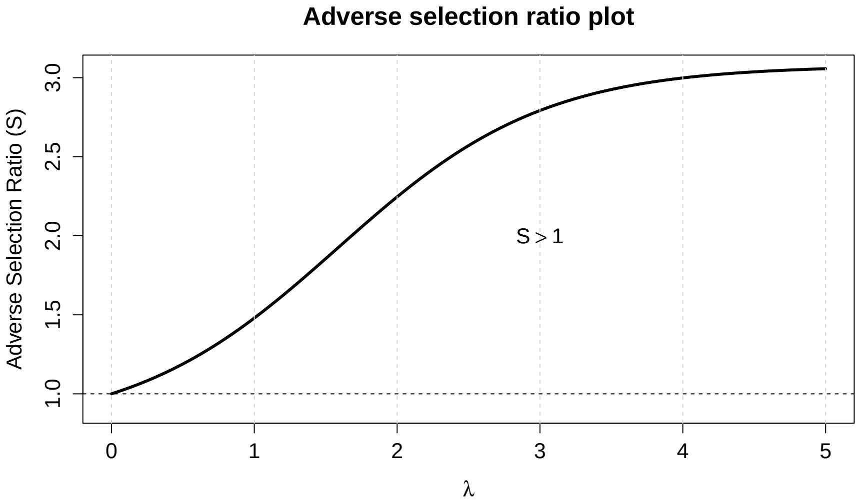
Results

Assumptions

- There are 2 risk-groups
- They have equal demand elasticities
  - Iso-elastic demand function: $\lambda_1 = \lambda_2 = \epsilon(\pi_e)$

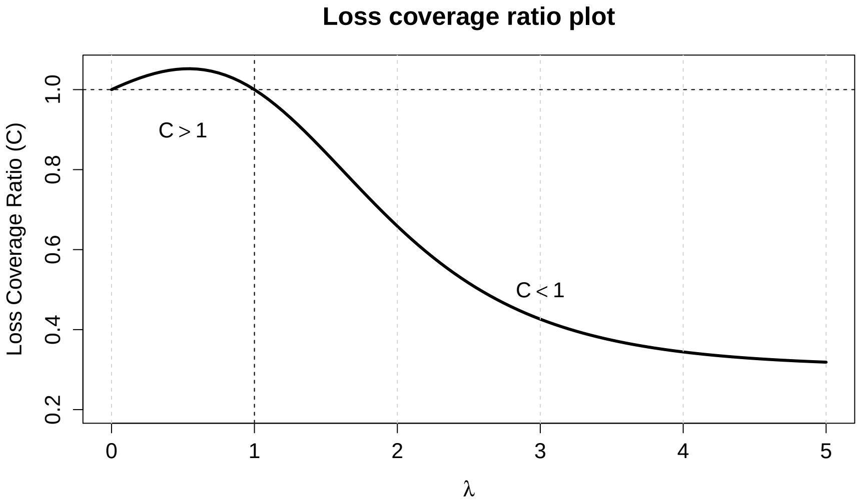
Results: Adverse Selection Ratio (S)

$p_1 = 9000, \tau_1 = 1, \mu_1 = 0.01; p_2 = 1000, \tau_2 = 1, \mu_2 = 0.04$



Results: Loss Coverage Ratio (C)

$p_1 = 9000, \tau_1 = 1, \mu_1 = 0.01; p_2 = 1000, \tau_2 = 1, \mu_2 = 0.04$



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Equilibrium Premium

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Different demand elasticities: multiple equilibria only arise under extreme conditions

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Multiple Equilibrium is rare in practical application.

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Summary

- When there is restriction on risk classification, a pooled premium π_e is charged across all risk-groups.
- There will always be adverse selection $\Rightarrow$ Adverse Selection may not be a good measure.
- Loss Coverage is an alternative metric.
  Using iso-elastic demand function,
- **Adverse Selection is not always a bad thing!**
  A moderate level of adverse selection can increase loss coverage.

Further Research

- Other/more general demand e.g. $d(\mu, \pi) = \tau e^{1-(\frac{\pi}{\mu})^{\lambda}}$.
- Loose restriction on demand elasticities.
- Partial restriction on risk classification.

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Questions?

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Thank you!