

LOSS COVERAGE IN INSURANCE MARKETS: WHY ADVERSE SELECTION IS NOT ALWAYS A BAD THING

MingJie Hao, Dr. Pradip Tapadar, Mr. Guy Thomas
University of Kent, UK

Email: mh586@kent.ac.uk, P.Tapadar@kent.ac.uk, R.G.Thomas@kent.ac.uk

IME 2015

Table of contents

Table of contents

- Background
 - ▶ How does insurance work?
 - ▶ Risk classification Scheme

Table of contents

- Background
 - ▶ How does insurance work?
 - ▶ Risk classification Scheme
- Adverse Selection

Table of contents

- Background
 - ▶ How does insurance work?
 - ▶ Risk classification Scheme
- Adverse Selection
- Loss Coverage

Table of contents

- Background
 - ▶ How does insurance work?
 - ▶ Risk classification Scheme
- Adverse Selection
- Loss Coverage
- Demand function
 - ▶ Iso-elastic demand function

Table of contents

- Background
 - ▶ How does insurance work?
 - ▶ Risk classification Scheme
- Adverse Selection
- Loss Coverage
- Demand function
 - ▶ Iso-elastic demand function
- Equilibrium Premium

Table of contents

- Background
 - ▶ How does insurance work?
 - ▶ Risk classification Scheme
- Adverse Selection
- Loss Coverage
- Demand function
 - ▶ Iso-elastic demand function
- Equilibrium Premium
- Results on adverse selection and loss coverage

Table of contents

- Background
 - ▶ How does insurance work?
 - ▶ Risk classification Scheme
- Adverse Selection
- Loss Coverage
- Demand function
 - ▶ Iso-elastic demand function
- Equilibrium Premium
- Results on adverse selection and loss coverage
- Summary and Further research

Table of contents

- Background
 - ▶ How does insurance work?
 - ▶ Risk classification Scheme
- Adverse Selection
- Loss Coverage
- Demand function
 - ▶ Iso-elastic demand function
- Equilibrium Premium
- Results on adverse selection and loss coverage
- Summary and Further research
- References

Table of contents

- Background
 - ▶ How does insurance work?
 - ▶ Risk classification Scheme
- Adverse Selection
- Loss Coverage
- Demand function
 - ▶ Iso-elastic demand function
- Equilibrium Premium
- Results on adverse selection and loss coverage
- Summary and Further research
- References

Background

How insurance works and risk classification scheme

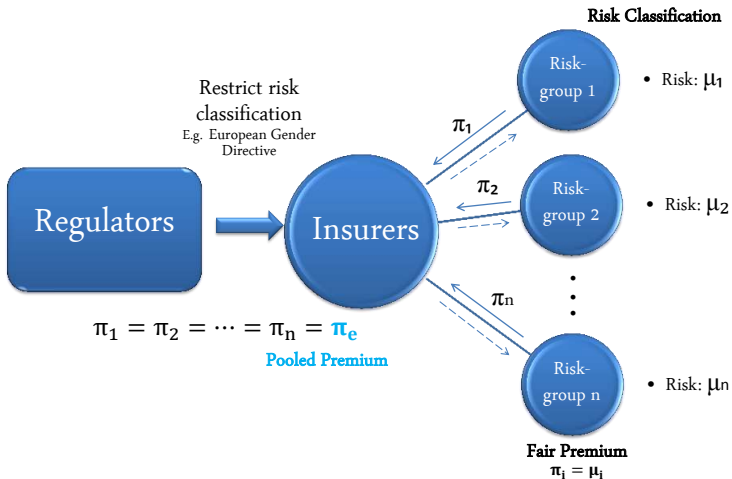


Table of contents

- Background
 - ▶ How does insurance work?
 - ▶ Risk classification Scheme
- **Adverse Selection**
- Loss Coverage
- Demand function
 - ▶ Iso-elastic demand function
- Equilibrium Premium
- Results on adverse selection and loss coverage
- Summary and Further research
- References

Adverse Selection

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

Adverse Selection

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

Typical definition

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

Adverse Selection

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

Typical definition

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

- Empirical results are mixed and vary by market.

Adverse Selection

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

Typical definition

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

- Empirical results are mixed and vary by market.

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

Adverse Selection

- Restricting risk classification \Rightarrow Policy is over-subscribed by high risks **BAD?**

Adverse Selection

- Restricting risk classification \Rightarrow Policy is over-subscribed by high risks **BAD?**
- **Good measure?**

Adverse Selection

- Restricting risk classification \Rightarrow Policy is over-subscribed by high risks **BAD?**
- **Good measure?**

Definition

$$\text{Adverse Selection (AS)} = \frac{\text{expected claim per policy}}{\text{expected loss per risk}} \quad (1)$$

Adverse Selection

- Restricting risk classification \Rightarrow Policy is over-subscribed by high risks **BAD?**
- **Good measure?**

Definition

$$\text{Adverse Selection (AS)} = \frac{\text{expected claim per policy}}{\text{expected loss per risk}} \quad (1)$$

$$\text{Adverse Selection Ratio: } \mathcal{S} = \frac{\text{AS at pooled premium } \pi_e}{\text{AS at risk-differentiated premiums}} \quad (2)$$

Adverse Selection

- Restricting risk classification \Rightarrow Policy is over-subscribed by high risks **BAD?**
- Good measure?**

Definition

$$\text{Adverse Selection (AS)} = \frac{\text{expected claim per policy}}{\text{expected loss per risk}} \quad (1)$$

$$\text{Adverse Selection Ratio: } \mathcal{S} = \frac{\text{AS at pooled premium } \pi_e}{\text{AS at risk-differentiated premiums}} \quad (2)$$

$> 1 \Rightarrow$ **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

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

No adverse selection.

Example

Restriction on risk classification-Case 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 (π_e)	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 (π_e)	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 (π_e)	0.02154	0.02154	0.02154
Numbers insured	200(400)	125(100)	325(500)
Adverse Selection Ratio (S)			1.3462 > 1

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 (π_e)	0.02154	0.02154	0.02154
Numbers insured	200(400)	125(100)	325(500)
Adverse Selection Ratio (S)			1.3462 > 1

Heavier adverse selection

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 (π_e)	0.02154	0.02154	0.02154
Numbers insured	200(400)	125(100)	325(500)
Adverse Selection Ratio (S)			1.3462 > 1

Heavier adverse selection

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

Table of contents

- Background
 - ▶ How does insurance work?
 - ▶ Risk classification Scheme
- Adverse Selection
- **Loss Coverage**
- Demand function
 - ▶ Iso-elastic demand function
- Equilibrium Premium
- Results on adverse selection and loss coverage
- Summary and Further research
- References

Loss Coverage

Loss Coverage

- Aim of insurance: provide protection for those who suffer losses.

Loss Coverage

- Aim of insurance: provide protection for those who suffer losses.
 - ▶ High risks most need insurance.
 - ▶ Restriction on risk classification seems reasonable.

Loss Coverage

- Aim of insurance: provide protection for those who suffer losses.
 - ▶ High risks most need insurance.
 - ▶ Restriction on risk classification seems reasonable.
- Thomas (2008, 2009) “**Loss Coverage**”:

Loss Coverage

- Aim of insurance: provide protection for those who suffer losses.
 - ▶ High risks most need insurance.
 - ▶ Restriction on risk classification seems reasonable.
- Thomas (2008, 2009) “**Loss Coverage**”:

Definition

$$\text{Loss Coverage (LC)} = \frac{\text{insured expected losses}}{\text{population expected losses}} \quad (3)$$

Loss Coverage

- Aim of insurance: provide protection for those who suffer losses.
 - ▶ High risks most need insurance.
 - ▶ Restriction on risk classification seems reasonable.
- Thomas (2008, 2009) “**Loss Coverage**”:

Definition

$$\text{Loss Coverage (LC)} = \frac{\text{insured expected losses}}{\text{population expected losses}} \quad (3)$$

$$\begin{aligned} \text{Loss Coverage Ratio: } C &= \frac{\text{LC at a pooled premium } \pi_e}{\text{LC at at risk-differentiated premium } \pi_i} \quad (4) \\ &> 1, \text{ **Favorable!**} \end{aligned}$$

Example

No restriction on risk classification

Example

No restriction on 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
Insured losses	4	4	8
LC (π_i) = LC (π_e)			8/16
Loss coverage ratio (C)			1

Example

No restriction on 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
Insured losses	4	4	8
LC (π_i) = LC (π_e)			8/16
Loss coverage ratio (C)			1

No adverse selection.

Example

Restriction on risk classification-Case 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 (π_e)	0.02	0.02	0.02
Numbers insured	300(400)	150(100)	450(500)
Insured losses	3	6	9
LC (π_e)			9/16
LC (π_i)			8/16
Loss coverage ratio (C)			1.125 > 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 (π_e)	0.02	0.02	0.02
Numbers insured	300(400)	150(100)	450(500)
Insured losses	3	6	9
LC (π_e)			9/16
LC (π_i)			8/16
Loss coverage ratio (C)			1.125 > 1

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

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 (π_e)	0.02154	0.02154	0.02154
Numbers insured	200(400)	125(100)	325(500)
Insured losses	2	5	7
LC (π_e)			7/16
LC (π_i)			8/16
Loss coverage ratio (C)			0.875 < 1

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 (π_e)	0.02154	0.02154	0.02154
Numbers insured	200(400)	125(100)	325(500)
Insured losses	2	5	7
LC (π_e)			7/16
LC (π_i)			8/16
Loss coverage ratio (C)			0.875 < 1

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

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 (π_e)	0.02154	0.02154	0.02154
Numbers insured	200(400)	125(100)	325(500)
Insured losses	2	5	7
LC (π_e)			7/16
LC (π_i)			8/16
Loss coverage ratio (C)			0.875 < 1

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

Table of contents

- Background
 - ▶ How does insurance work?
 - ▶ Risk classification Scheme
- Adverse Selection
- Loss Coverage
- Demand function
 - ▶ Iso-elastic demand function
- Equilibrium Premium
- Results on adverse selection and loss coverage
- Summary and Further research
- References

Demand Function

Definition

$d(\mu, \pi)$: the proportional demand for insurance for risk μ at premium π .

Demand Function

Definition

$d(\mu, \pi)$: the proportional demand for insurance for risk μ at premium π .

It is assumed to have the following properties:

- $\frac{\partial}{\partial \pi} d(\mu, \pi) < 0$: a decreasing function of premium.

Demand Function

Definition

$d(\mu, \pi)$: the proportional demand for insurance for risk μ at premium π .

It is assumed to have the following properties:

- $\frac{\partial}{\partial \pi} d(\mu, \pi) < 0$: a decreasing function of premium.
- $d(\mu_1, \pi) < d(\mu_2, \pi)$: the proportional demand is greater for the higher risk-group.

Demand Function

Definition

$d(\mu, \pi)$: the proportional demand for insurance for risk μ at premium π .

It is assumed to have the following properties:

- $\frac{\partial}{\partial \pi} d(\mu, \pi) < 0$: a decreasing function of premium.
- $d(\mu_1, \pi) < d(\mu_2, \pi)$: the proportional demand is greater for the higher risk-group.

Definition

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

$$\epsilon(\mu, \pi) = \lambda, \text{ i.e. constant} \quad (5)$$

Demand Function

Iso-elastic demand function

$$\epsilon(\mu, \pi) = \lambda, \text{ i.e. constant} \quad (5)$$

$$d(\mu, \pi) = \tau \left[\frac{\pi}{\mu} \right]^{-\lambda}. \quad (6)$$

Iso-elastic demand function

$\tau = 1, \mu = 0.01, \lambda = 0.4, 0.8$ and 1.2

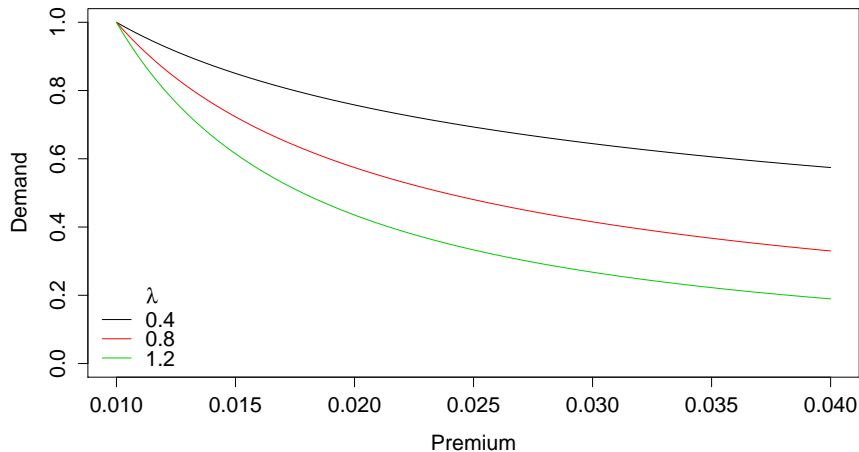


Table of contents

- Background
 - ▶ How does insurance work?
 - ▶ Risk classification Scheme
- Adverse Selection
- Loss Coverage
- Demand function
 - ▶ Iso-elastic demand function
- **Equilibrium Premium**
- Results on adverse selection and loss coverage
- Summary and Further research
- References

Equilibrium Premium

Equilibrium premium, π_e , ensures a zero expected total profit,

Equilibrium Premium

Equilibrium premium, π_e , ensures a zero expected total profit, i.e.

$$d(\mu_1, \pi_e)(\pi_e - \mu_1)p_1 + d(\mu_2, \pi_e)(\pi_e - \mu_2)p_2 = 0. \quad (7)$$

Equilibrium Premium

Equilibrium premium, π_e , ensures a zero expected total profit, i.e.

$$d(\mu_1, \pi_e)(\pi_e - \mu_1)p_1 + d(\mu_2, \pi_e)(\pi_e - \mu_2)p_2 = 0. \quad (7)$$

“Profit” from low risk-group = “Loss” from high risk-group

Equilibrium Premium

Equilibrium premium, π_e , ensures a zero expected total profit, i.e.

$$d(\mu_1, \pi_e)(\pi_e - \mu_1)p_1 + d(\mu_2, \pi_e)(\pi_e - \mu_2)p_2 = 0. \quad (7)$$

“Profit” from low risk-group = “Loss” from high risk-group

$$d(\mu_i, \pi_e) = \tau_i \left[\frac{\pi_e}{\mu_i} \right]^{-\lambda_i}, \quad i = 1, 2$$

Equilibrium Premium

Equilibrium premium, π_e , ensures a zero expected total profit, i.e.

$$d(\mu_1, \pi_e)(\pi_e - \mu_1)p_1 + d(\mu_2, \pi_e)(\pi_e - \mu_2)p_2 = 0. \quad (7)$$

“Profit” from low risk-group = “Loss” from high risk-group

$$d(\mu_i, \pi_e) = \tau_i \left[\frac{\pi_e}{\mu_i} \right]^{-\lambda_i}, \quad i = 1, 2$$

If $\lambda_1 = \lambda_2 = \lambda$,

Equilibrium Premium

Equilibrium premium, π_e , ensures a zero expected total profit, i.e.

$$d(\mu_1, \pi_e)(\pi_e - \mu_1)p_1 + d(\mu_2, \pi_e)(\pi_e - \mu_2)p_2 = 0. \quad (7)$$

“Profit” from low risk-group = “Loss” from high risk-group

$$d(\mu_i, \pi_e) = \tau_i \left[\frac{\pi_e}{\mu_i} \right]^{-\lambda_i}, \quad i = 1, 2$$

If $\lambda_1 = \lambda_2 = \lambda$,

$$\pi_e = \frac{\alpha_1 \mu_1^{\lambda+1} + \alpha_2 \mu_2^{\lambda+1}}{\alpha_1 \mu_1^\lambda + \alpha_2 \mu_2^\lambda}, \quad (8)$$

where

$$\alpha_i = \frac{\tau_i p_i}{\tau_1 p_1 + \tau_2 p_2}, \quad i = 1, 2 \quad (9)$$

(Fair-premium demand-share)

Table of contents

- Background
 - ▶ How does insurance work?
 - ▶ Risk classification Scheme
- Adverse Selection
- Loss Coverage
- Demand function
 - ▶ Iso-elastic demand function
- Equilibrium Premium
- **Results on adverse selection and loss coverage**
- Summary and Further research
- References

Results on adverse selection

Results on adverse selection

Adverse Selection Ratio

$$S = \frac{\pi e}{\alpha_1 \mu_1 + \alpha_2 \mu_2}. \quad (10)$$

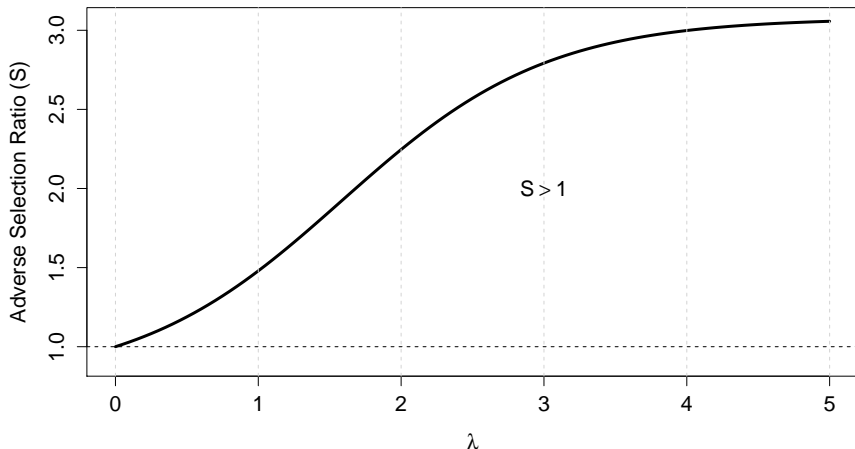
$$\alpha_i = \frac{\tau_i p_i}{\tau_1 p_1 + \tau_2 p_2}, i = 1, 2$$

(Fair-premium demand-share)

Results: Adverse Selection Ratio (S)

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

Adverse selection ratio plot



Results on loss coverage

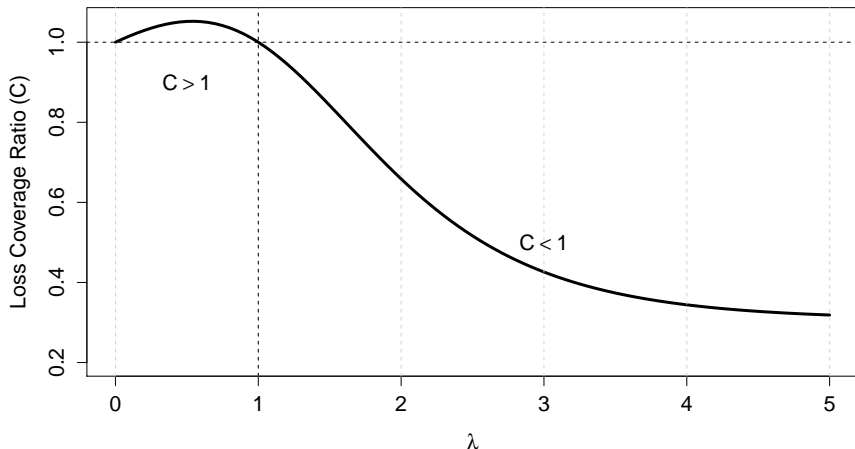
Loss Coverage Ratio

$$C = \frac{1}{\pi e^\lambda} \frac{\alpha_1 \mu_1^{\lambda+1} + \alpha_2 \mu_2^{\lambda+1}}{\alpha_1 \mu_1 + \alpha_2 \mu_2}. \quad (11)$$

Results: Loss Coverage Ratio (C)

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

Loss coverage ratio plot



Results: Loss Coverage Ratio (C)

$p_1 = 9000, \tau_1 = 1, \mu_1 = 0.01; p_2 = 1000, \tau_2 = 1, \mu_2 = 0.03, 0.04, 0.05, 0.08$

Loss coverage ratio plot

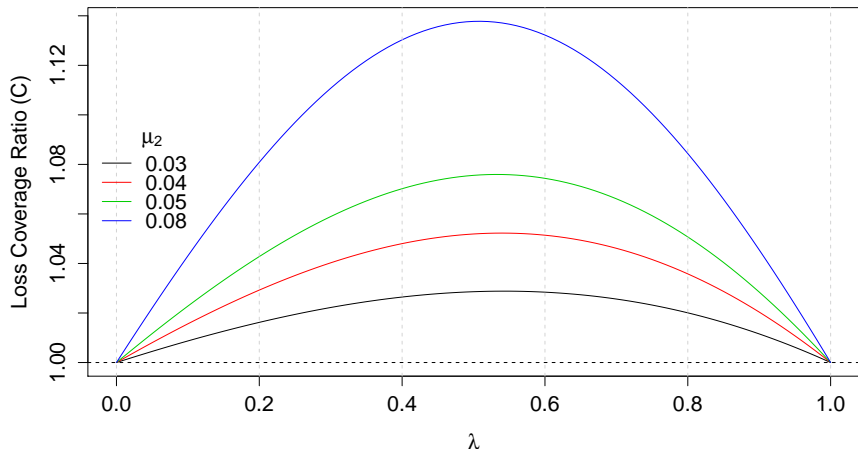


Table of contents

- Background
 - ▶ How does insurance work?
 - ▶ Risk classification Scheme
- Adverse Selection
- Loss Coverage
- Demand function
 - ▶ Iso-elastic demand function
- Equilibrium Premium
- Results on adverse selection and loss coverage
- **Summary and Further research**
- References

Summary

Summary

- When there is restriction on risk classification, a **pooled premium** π_e is charged across all risk-groups.

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.

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.

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.
- **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.

References

- Hao, M. *et al* (2015) Insurance Loss Coverage Under Restricted Risk Classification: The Case Of Iso-elastic Demand. *Submitted for publication*.
- Cardon, J. H. and Hendel, I. (2001) Asymmetric Information in Health Insurance: Evidence from the National Medical Expenditure Survey. *Rand J. Econ.* 32 (Autumn): 408-27.
- Cawley, J. and Philipson, T. (1999) An Empirical Examination of Information Barriers to Trade in Insurance. *A.E.R.* 89 (September): 827-46.
- Chiappori, P. A. and Salanie, B. (2000) Testing for Asymmetric Information in Insurance Markets, *The Journal of Political Economy*, 108, 1; 56-78.
- Cohen, A. (2005) Asymmetric Information and Learning: Evidence from the Automobile Insurance market. *Rev. Eco. Statis.* 87 (June):197-207.

References

- Finkelstein, A. and Poterba (2004) Adverse Selection in Insurance markets: Policyholder Evidence from the U.K. Annuity Market. *J.P.E.* 112 (February): 183-208.
- Thomas, R. G. (2008) Loss Coverage as a Public Policy Objective for Risk Classification Schemes. *The Journal of Risk and Insurance*, 75(4), pp. 997-1018.
- Thomas, R. G. (2009) Demand Elasticity, Adverse Selection and Loss Coverage: When Can Community Rating Work? *ASTIN Bulletin*, 39(2), pp. 403-428.

Questions?

Questions?

Thank you!