Loss coverage: beneficial 'adverse' selection

Why insurance may work better with less risk classification

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In discussions relating to health or life insurance or genetic testing, the mantra of 'adverse selection' is often invoked as an argument against any restrictions on risk classification. The argument is that any restrictions will tend to lead to more insurance bought by higher risks, and less insurance bought by lower risks, so that the equilibrium price of insurance will rise; and as the number of higher risks is usually small relative to the number of lower risks, the overall number insured will fall. Insurers suggest, either explicitly or implicitly, that any adverse selection and any fall in numbers insured should be regarded as a bad outcome from a public policy viewpoint. But this argument that all adverse selection is bad rests on a mis-measure of the benefit of insurance to the population as a whole. A fall in the number of people insured can be consistent with a higher number of losses compensated by insurance, *if more of the 'right' people (those more likely to suffer loss) buy insurance.* From a public policy perspective, a degree of so-called 'adverse' selection in insurance can be beneficial.

To see this point, consider some simple numerical examples. Suppose that in a population of 1,000, 16 people die every year. Suppose that 200 people have private knowledge (such as a genetic test result) which tells them that they have a risk of dying 4 times higher than the other 800 people. Assume that everyone can buy either one unit of life insurance or none (this assumption simplifies the presentation, but it is not necessary[1]). If test results are disclosed, insurers will charge different prices to standard and high risks. Suppose that under these conditions, exactly half of each group buys insurance. Table 1 shows the outcome: 8 of the 16 deaths in the whole population are compensated by insurance. This 50% 'loss coverage' is an index of the social benefit of insurance to the population as a whole.

Table 1 Insurers discriminate: no adverse selection

	Standard risk	**High risk**
Population:	800	200
Risk:	1/100	4/100
Break-even premiums (differentiated):	1/100	4/100
Insurance purchases:	400	100
Deaths compensated by insurance:	4	4
Loss coverage: $\left(\frac{deaths\ \ insured}{total\ \ deaths}\right)$	50%	

Now suppose instead that insurers are banned from differentiating prices by risk, and so they have to charge a single 'pooled' price to both the standard and high risks. One possible outcome is shown in Table 2. The 'pooled' price is expensive for standard risks, so fewer of them buy insurance (300, compared with 400 before). The 'pooled' price is also cheaper for high risks, so more of them buy insurance (150, compared with 100 before). Because there are 4 times as many standard risks as high risks in the population, the total number of policies sold falls (450, compared with 500 before). This is adverse selection, and insurers often assert that it must always be bad. But in this case, the shift in coverage towards high risks more than outweighs the fall in number of policies sold: 9 of the 16 deaths (56%) in the population as a whole are now compensated by insurance (compared with 8 of 16 before). A moderate degree of adverse selection has led to higher loss coverage – a good outcome.

Table 2 Insurance discrimination banned: moderate adverse selection leading to increased loss coverage (good outcome)

	Standard risk	High risk
Population:	800	200
Risk:	1/100	4/100
Break-even premium (pooled):	← 2/100 →	
Insurance purchases:	300	150
Deaths compensated by insurance:	3	6
Loss coverage: $\left(\frac{deaths\ \ insured}{total\ \ deaths}\right)$	56%	

However, if the adverse selection becomes too severe, this can lead to a bad outcome. This possibility is shown in Table 3. Only 200 of the standard risks and 125 of the high risks buy insurance, giving a total number of policies sold of 325. The shift in coverage towards high risks is insufficient to outweigh the fall in number of policies sold: only 7 of the 16 deaths (44%) in the population are now compensated by insurance (compared with 8 of 16 in Table 2, and 9 of 16 in Table 3). The high degree of adverse selection has led to lower loss coverage – a bad outcome.

Table 3 Insurance discrimination banned: severe adverse selection leading to reduced loss coverage (bad outcome)

	Standard risk	High risk
Population:	800	200
Risk:	1/100	4/100
Break-even premium (pooled):	← 2.15/100 →	
Insurance purchases:	200	125
Deaths compensated by insurance:	2	5
Loss coverage: $\left(\frac{deaths\ \ insured}{total\ \ deaths}\right)$	44%	

Which of Tables 2 or 3 represents the more likely outcome if restrictions are imposed on insurance discrimination? The answer depends on the relative numbers in the high and low risk groups, their relative risks, and an economic quantity known as *elasticity of demand* for insurance in the higher and lower risk groups. Elasticity of demand is the percentage change in insurance demand for a 1% change in price; it is a measure of the responsiveness of insurance purchasing behavior to changes in price. These dependencies are explored in recent papers in the insurance and actuarial literature (Thomas, 2007, 2008, 2009). Preliminary simulation studies suggest that with plausible elasticities of demand in high and low risk groups, a ban on access to test results may often increase loss coverage; but the converse outcome is also possible.

Under the loss coverage criterion, public policy on risk classification can be seen as a question of degree: what degree of restriction on risk classification is required to induce the optimal degree of adverse selection, which maximizes the loss coverage? For example, some restrictions on the use of genetic tests seem likely to increase loss coverage; and further restrictions, extending to some other categories of information, might also increase loss coverage; but if the use of age as a risk factor was also restricted, this might 'go too far,' reducing loss coverage. The optimal degree of risk classification is an empirical matter, and the answer is likely to differ for different types of insurance. But the important points of principle for public policymakers are that (a) 'optimal' should mean optimal *from a public policy perspective*, which means (arguably) maximizing loss coverage; (b) there is no reason to expect that unrestricted competition between insurers in risk classification will maximize loss coverage.

Loss coverage is not suggested as the only criterion which public policymakers should consider when setting policy on risk classification. The possible 'spillover' effects of discrimination in insurance on privacy, public health, and discrimination in other fields such as employment and home ownership may also be considered. However, to the extent that the effects within the insurance market itself are given weight, policymakers should carefully consider the metric they use to measure these effects. From a public policy perspective, loss coverage may be a better metric than the number of policies sold. This is because loss coverage focuses on the expected losses compensated by insurance (risk-weighted insurance demand), which seems a better indicator of the social efficacy or benefit of insurance to the whole population than number of policies sold (un-weighted insurance demand).

Finally, note that even if the reality of a particular market corresponds to Table 3 – that is, restrictions on risk classification have 'gone too far,' reducing loss coverage – the 'cost' of the restrictions as measured by loss coverage is smaller than the 'cost' measured by reduction in number of policies sold. This again emphasizes the importance of policymakers carefully considering the metric used to measure the effects of risk classification policies.

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References

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Footnotes

[1] The assumption of a uniform sum insured simplifies the presentation, but it is not necessary: the argument can be re-worked in terms of money-demand for insurance. Where the individual can choose any sum insured, it is sometimes suggested that customers with private knowledge (say from a genetic test) will rationally exploit this by buying a very large policy, or multiple policies. But for plausible probabilities and premiums, this concern seems misconceived, because *the individual can make the bet only once.* For example, suppose that the standard probability of claim $p = 0.01$, but I have private knowledge that my own $p = 0.04$. If I buy a very large insurance policy, I have to pay the very large premium, and it almost certain (96% certain, on the true probabilities) that I just lose the premium. This seems to me an unattractive proposition. In my view, over-insurance is generally unattractive, unless the probability of claim approaches a certainty (say $p > 0.75$). The notion that private knowledge of substantially higher risk always makes a large bet on over-insurance attractive has been called the *fallacy of the one-shot gambler* (Thomas 2007).