UK response to the European Court of Justice ruling that insurance benefits and premiums after 21 December 2012 should be gender-neutral

Consultation Response

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SUMMARY

The approach taken in the impact assessment appears to be broadly as follows. Compare the equilibrium unisex premium with adverse selection after the ban to the weighted average of the male and female prices before the ban; label the difference as the “cost” of banning gender classification.

This is not reasonable, because it ignores the point that the increase in premiums (costs to consumers) arising from adverse selection corresponds to an increase in claims (benefits to consumers). Only any *excess* increase, over and above any increase in claims arising from the adverse selection, should be regarded as a cost to consumers.[1]

In the transitional period after the ban, some insurers may apply opportunistic rate increases in excess of any expected increase in claims arising from adverse selection. But in the long run, competition should ensure that for most classes of insurance, the sustainable level of this excess increase is very small.

An important aspect not covered in the impact assessment is the effect of the ban on the compensation of losses. If the ban leads to adverse selection, this means that coverage is shifted towards the higher risk gender (those who have greater need of the insurance) and away from the lower risk gender. Provided that the total number of policies sold does not fall too much (the adverse selection is not too severe), the fraction of the whole population’s losses which is compensated by insurance will increase (the *loss coverage* will increase). This is a possible benefit of banning gender classification.

The main points above are elaborated in an example below.

[1] In the motor insurance assessment, this problem is avoided by assumption: all those with a driving licence hold a policy both before and after the change, *ie* no adverse selection.

BANNING GENDER CLASSIFICATION: AN EXAMPLE

The approach taken in the impact assessment appears to be broadly as follows. Compare the equilibrium unisex premium with adverse selection after the ban to the weighted average of the male and female prices before the ban; label the difference as the "cost" of banning gender classification. The example highlights a drawback in this approach. It also demonstrates that it is possible that the ban will increase *loss coverage*, defined as

$$\text{Loss coverage} = \frac{\textit{Losses compensated by insurance}}{\textit{Total population losses}}$$

If the restitution of losses by insurance has positive social value – that is, the widely accepted notion that compensation of losses by insurance is generally a "good thing" – then higher loss coverage could be seen as a benefit of banning gender classification.

Two presentations of the example are given: first a simplified version in tables, and then a simulation.

(a) TABLES

Assume 100 women with risk 0.1 and 100 men with risk 0.2, and that with gender-differentiated premiums exactly half of each gender buy insurance.[2] Assume fixed sums insured and ignore insurers' profit margins[3]. Table 1 shows the outcome under gender-differentiated pricing. The total premiums collected (and benefits paid) are 50 x 0.1 + 50 x 0.2 = 15.

Table 1: Gender-differentiated premiums (no adverse selection)

	Women	Men
Population:	100	100
Risk:	0.1	0.2
Break-even premium (pooled):	0.1	0.2
Insurance purchases:	50	50
Losses compensated by insurance:	5	10
Loss coverage: $\left(\frac{\textit{compensated losses}}{\textit{total losses}}\right)$	50%	

Then ban gender classification. One possible outcome is shown in Table 2. Adverse selection implies that the number of female purchasers falls (say to 40), and the number of make purchasers rises (say to 60). The total premiums collected are 16. In the new equilibrium, the break-even premium charged is 16/100 = 0.16.

This is higher than the population-weighted average of the previous gender-differentiated premiums (0.15). If we took the approach of the impact assessment, we would label this difference as a "cost" to consumers. But this cannot sensibly be called a "cost," because it also reflects the compensation of a larger number of losses (16 instead of 15).

[2] This assumption is arbitrary, but it roughly corresponds to UK life insurance: approximately half the population holds some life insurance.
[3] These assumptions simplify the presentation, but they are not necessary for the argument.

The compensation of 16 losses (compared with 15 before) raises the loss coverage for the whole population to 16/30 = 53.33%. This could be seen as a better outcome from banning gender classification.

Table 2: Moderate adverse selection, higher loss coverage (better outcome)

	Women	Men
Population:	100	100
Risk:	0.1	0.2
Break-even premium (pooled):	← 0.16 →	
Insurance purchases:	40	60
Losses compensated by insurance:	4	12
Loss coverage: $\left(\dfrac{\textit{compensated losses}}{\textit{total losses}}\right)$	53.33%	

However if adverse selection is severe, this can lead to a fall in loss coverage. This possibility is shown in Table 3. The number of female purchasers falls more drastically, say to 20, whilst the number of male purchasers rises to 60 as before. The new break-even premium is 14/80 = 0.1875.

The compensation of 14 losses (compared with 15 originally) reduces the loss coverage to 14/30 = 46.67%. This lower loss coverage could be viewed as a worse outcome from banning gender classification.

Table 3: Severe adverse selection, lower loss coverage (worse outcome)

	Women	Men
Population:	100	100
Risk:	0.1	0.2
Break-even premium (pooled):	← 0.14 →	
Insurance purchases:	20	60
Losses compensated by insurance:	2	12
Loss coverage: $\left(\dfrac{\textit{compensated losses}}{\textit{total losses}}\right)$	46.67%	

Which of the stylised examples in Table 2 (good) or Table 3 (bad) corresponds more closely to the actual outcome of a ban? The answer depends on the relative numbers, risks and insurance demand elasticities for men and women. Figures for numbers and risks are routinely measured by insurers; demand elasticities are not,[4] but for several classes of

[4] Insurers may estimate demand elasticity when pricing highly competitive classes such as motor insurance, but we need to distinguish between *cross-firm* and *cross-product* elasticities. The *cross-firm* demand elasticity for motor insurance sold via a price aggregator site may be as high as 10 or 20 (because the customer has many substitutes for buying insurance from any *one* firm). But the *cross-product* demand elasticity for motor insurance may be very low, perhaps less than 0.1 (because there are no good substitutes for buying motor insurance from *at least one* firm). It is the cross-product elasticity that is relevant in assessing the effect of a market-wide ban.

insurance there is some evidence (discussed later in this note) for values in the range 0.2 to 0.7. In the absence of any better evidence, we will now show results for simulation with elasticities in the slightly wider range 0 to 1.0.

(b) SIMULATION

This section uses the same {male:female} relative populations {50:50} and relative risks {2:1} as above. It assumes a plausible insurance demand function with an elasticity parameter. Simulations can then illustrate the effect of different values of the elasticity parameter for men and women. There are two main effects of interest: the effect on the equilibrium premium, and the effect on the corresponding loss coverage. The take-away result is that with plausible demand elasticities, loss coverage will be increased by banning gender classification; but if demand elasticities are too high, loss coverage could fall.

The insurance demand function is as follows:

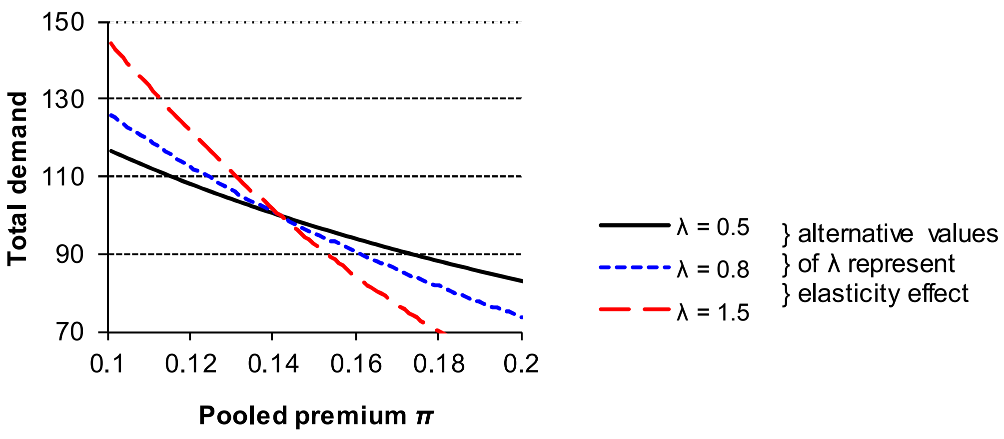
$$d_i(\pi) = P_i e^{1-(\pi/\mu_i)^{\lambda_i}} \qquad i=1,2$$

where

- i = 1,2 are two populations (say men and women)
- $d_i(\pi)$ = demand from population i as a function of the unisex premium π
- P_i is the number of members of the population of risk class i who buy insurance at an actuarially fair premium,[5] that is when $\pi = \mu_i$
- μ_i is the risk (expectation of claim) for population i
- λ_i is an elasticity parameter for insurance demand of population i.

The sample demand curves in Figure 1 illustrate how the value of the elasticity parameter λ_i controls the shape of the demand curve.

Figure 1 Demand curves for specimen values of fair-premium elasticity λ_i



[5] The specification of P_i as the *number* of members of population i who buy insurance at an actuarially fair premium assumes that all insurance is for unit sum assured. This simplification is convenient for exposition, but it is not necessary: P_i could alternatively be regarded as the fair-premium money demand for insurance from population i.

The price elasticity of demand d_i with respect to π can be written as the log-log derivative:

$$\left| \frac{\partial \ln[d_i(\pi)]}{\partial \ln \pi} \right| = \lambda_i \, (\pi / \mu_i)^{\lambda_i}$$

where we have taken absolute values to eliminate the minus sign. Note that the parameter λ_i represents the price elasticity of demand for insurance from population i when $\pi = \mu_i$, that is when the premium is equal to population i's gender-differentiated risk. Hence λ_i can be thought of as the **"fair-premium demand elasticity".** This corresponds to empirical estimates of demand elasticity from extant gender-differentiated markets.

We would generally expect fair-premium demand elasticity to be at least marginally higher for the higher-risk gender (here, men). This is because the price of insurance for them is higher relative to the prices other goods and services, and so insurance absorbs a larger part of their total budget constraint.

It is convenient to define a "base" λ_1 for the lower-risk group (here, women) and then set

$$\lambda_2 = \left(\frac{\mu_2}{\mu_1} \right)^{\alpha} \lambda_1 \qquad (1)$$

where α is an index for the male-female difference in fair-premium demand elasticity. There are no absolute theoretical limits on the value of α, but $0 \le \alpha \le 1$ may be a reasonable range –

– if $\alpha = 0$, fair-premium demand elasticity is the same for both risk groups;
– if $\alpha = 1$, twice the risk gives twice the fair-premium demand elasticity.

The graphs in Figure 2 show the equilibrium premium and loss coverage after gender classification is banned. Figures 2 (a), (b) and (c) correspond respectively to $\alpha = 0$, 1/3 and 2/3, that is nil, modest and substantial male-female differentials in fair-premium demand elasticity. It can be seen that the pattern of results is similar for all three values.

In the left-hand panels of Figure 2, the equilibrium premium after the ban (blue sloped line) is always above the population-weighted average premium (PWAP) before the ban (dashed horizontal line). This reflects the shift in coverage towards higher risks under adverse selection.

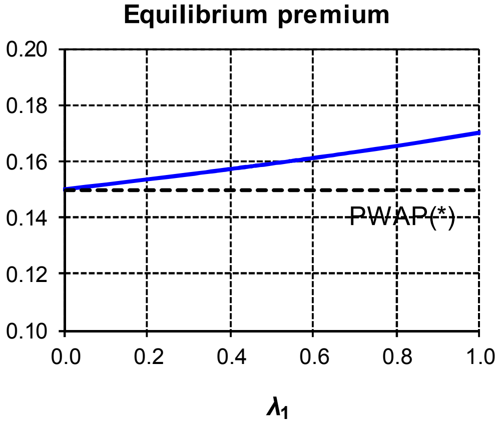
However, the impact of adverse selection on loss coverage is *not* necessarily adverse. In the right-hand panels of Figure 2, loss coverage after the ban (red curved line) can be higher or lower than before the ban (dashed horizontal line). Loss coverage is higher after the ban if demand elasticity is low enough. The critical values of (female) demand elasticity below which we observe higher loss coverage after the ban are roughly 0.5, 0.7 and 0.9 in Figure (a), (b) and (c).

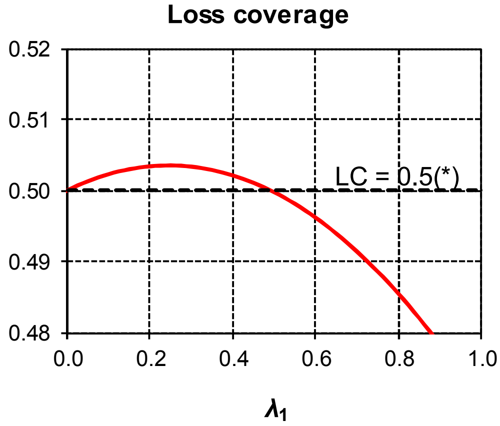
A larger difference in demand elasticity for men and women gives a better result (the red line is higher in the lower panels). This accords with our intuition: if men (facing a lower price) after the ban) buy a lot more insurance, and women (facing a higher price) buy only slightly less, then men's higher risk implies that more losses will end up being compensated.

Overall, Figure 2 shows the possibility that if demand elasticity is low enough, a ban on gender classification will lead to higher loss coverage than before the ban. This is a possible benefit of a ban.

Figure 2: Premium and loss coverage for specimen male/female elasticity differentials

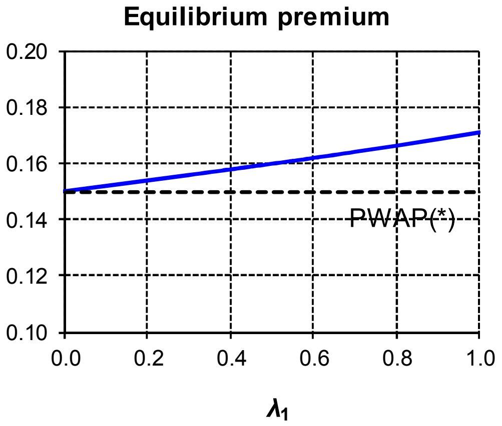
(a) with $\alpha = 0$ (*ie fair-premium demand elasticity* *__equal__* *for men and women*)

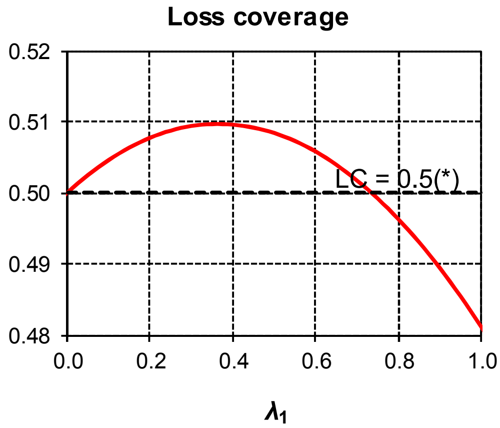




(b) with $\alpha = 1/3$ *(ie* *__modest male-female differential__* *in fair-premium demand elasticity*)

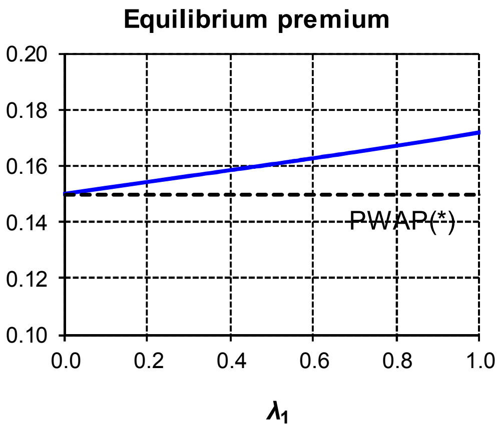
(*eg* if female elasticity 0.5, male 0.63; if female 0.7, male 0.88; etc)

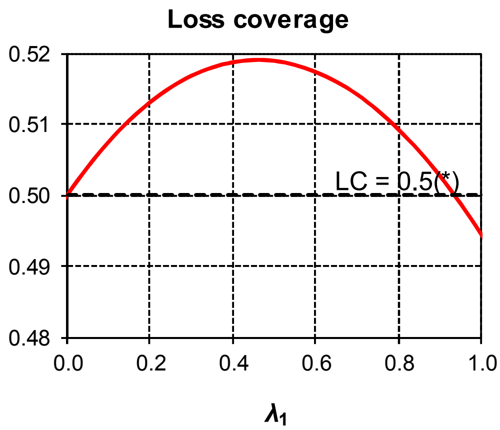




(c) with $\alpha = 2/3$ *(i.e* *__substantial male-female differential__* *in fair-premium demand elasticity)*

(*eg* if female elasticity 0.5, male 0.79; if female 0.7, male 1.11; etc)





(*) PWAP = population-weighted average premium

(*) LC = 0.5: loss coverage under gender-differentiated premiums

COMPARISON WITH EMPIRICAL DEMAND ELASTICITIES

The simulation results in Figure 2 can be compared with empirical estimates of demand elasticity for various classes of insurance, as follows:[6]

- For yearly renewable term life insurance in the US, an estimate of 0.4 to 0.5 has been reported (Pauly et al, 2003).
- A questionnaire survey about life insurance purchasing decisions produced an estimate of 0.66 (Viswanathan et al, 2007).
- For private health insurance in the US, several studies estimate demand elasticities in the range of 0 to 0.2 (Chernew et al., 1997; Blumberg et al., 2001; Buchmueller and Ohri, 2006).
- For private health insurance in Australia, Butler (1999) estimates demand elasticities in the range 0.36 to 0.50.

I do not know of any gender-differentiated demand elasticity data which could be used for further calibration of the above simulation. But the above figures are enough to show that the fair-premium demand elasticities required to produce an increase in loss coverage are plausible in comparison to those estimated in a range of previous empirical work.

OTHER COMMENTS ON THE IMPACT ASSESSMENT

I have some further comments on the impact assessment.

1. The impact assessment for motor insurance assumes no change in coverage, so all of the extra £300m premiums collected is profit. That is, profits are permanently increased by around 1.7% of premiums. Given the low single-digit profit margins which are typical in motor insurance, this could represent a near-doubling of long-term profit margins. This seems to me rather implausible, given that only one risk factor is being banned, and many factors which remain available (occupation, car group, etc) are strongly correlated with it.

2. One reason for this high estimate may be that it is based on Figure 13 (and possibly Figure 3) from the Oxera (2010) Report (reproduced as Figure 4 in the Consultation Document). Figure 15 in the same Oxera Report gives a very different impression: the increases for females are generally *less* than the reductions for males. The difference appears to be because Figure 15 (realistically) allows for other risk factors which are correlated with gender (occupation, car group, etc) to pick up part of the gender effect. Figure 13, on the other hand, is based on removing gender from pricing models without allowing other correlated rating factors to compensate.

3. Scattered throughout the impact assessment there are allusions to motor insurance having been loss-making in recent years, with this being suggested as a reason why male rates may not fall (*eg* middle of page 18; page 27, paragraph 20; page 28, paragraph 22). But any increases consequent on insurers' need to recoup past losses would apply equally if gender classification was *not* banned.

4. Finally, the impact assessment inevitably relies largely on figures supplied by the Association of British Insurers. Many members of this body have commercial incentives to exaggerate the impact of the ban, as a smokescreen for larger increases in premiums than the change actually justifies. It is not a proper function of Government to act as cheerleader for these exaggerations, to the detriment of consumers.

[6] All estimates are given here with the minus sign omitted.

FURTHER RESOURCES

(copies available at www.guythomas.org.uk/gender/gender.php)

1. For another discussion of the impact of banning gender classification (written *before* the Test Achats ruling):

Thomas, G. 'More Equal than Others?' *The Actuary*, March 2011.

2. For more details of the model used to produce the graphs in this note:

Thomas, R.G. (2009) 'Demand elasticity, risk classification and loss coverage: when can community rating work?' *ASTIN Bulletin*, **39**: 403-428.

3. For a technical introduction to the concept of loss coverage:

Thomas, R.G. (2008) 'Loss coverage as a public policy objective for risk classification schemes.' *Journal of Risk & Insurance* **75**: 997-1018.

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Buchmueller, T. C., Ohri, S. (2006) 'Health insurance take-up by the near-elderly' *Health Services Research*, **41**: 2054-2073.

Butler, J. R. (2002) 'Policy change and private health insurance: Did the cheapest policy do the trick?' *Australian Health Review,* **25**, 6: 33-41.

Chernew, M., Frick, K., & McLaughlin, C. (1997) 'The demand for health insurance coverage by low-income workers: Can reduced premiums achieve full coverage?' *Health Services Research*, **32**: 453-470.

Oxera (2010) *The use of gender in insurance pricing.* ABI Research Paper No. 24.

Pauly, M.V., Withers, K.H., Viswanathan, K.S., Lemaire, J., Hershey, J.C., Armstrong, K., and Asch, D.A. (2003) 'Price elasticity of demand for term life insurance and adverse selection', *NBER Working Paper,* **9925**.

Viswanathan, K.S., Lemaire, J., K. Withers, K., Armstrong, K., Baumritter, A., Hershey, J., Pauly, M., and Asch, D.A. (2006) 'Adverse selection in term life insurance purchasing due to the BRCA 1/2 Genetic Test and elastic demand' *Journal of Risk and Insurance*, **74**: 65-86.