The Australian Journal of Agricultural and Resource Economics, 44:1, pp. 83–106

Probability distributions for economic surplus changes: the case of technical change in the Australian wool industry

Xueyan Zhao, William E. Griffiths, Garry R. Griffith and John D. Mullen*

Mullen, Alston and Wohlgenant (1989) (MAW) examined the distribution of the benefits of technical change in the Australian wool industry. Their conclusions are revisited by examining the probability distributions of changes in the welfare measures, given uncertainty about their model parameters. Subjective probability distributions are specified for the parameters and correlations among some of the parameters are imposed. Hierarchical distributions are also used to model diverse views about the specification of the subjective distributions. A sensitivity elasticity is defined through the estimation of a response surface to measure the sensitivity of the estimated research benefits to individual parameters. MAW's conclusions are found to be robust under the stochastic approach to sensitivity analysis demonstrated in this article.

1. Introduction

The returns from new technologies are typically measured by changes in economic surplus areas. The estimated price and quantity changes required for the surplus calculations are taken from structural econometric models if possible, but often such models are not available. In these circumstances, synthetic models, also called equilibrium displacement models (EDM), can be used instead (for example, Muth 1964; Freebairn, Davis and Edwards 1982; and Alston 1991). The estimation of research benefits using this approach relies in part on the specification of a set of market parameters that describe demand and supply responsiveness in the industry. In most EDM applications, the choice of these market parameters is based on published

* Xueyan Zhao and William Griffiths are PhD student and Professor of Econometrics, respectively, in the Graduate School of Agricultural and Resource Economics, University of New England. Garry Griffith is Adjunct Professor in the Graduate School of Agricultural and Resource Economics, University of New England, Australia, and Principal Research Scientist in NSW Agriculture, Armidale. John Mullen is Senior Research Scientist in NSW Agriculture, Orange. We are grateful to Professor Roley Piggott for many insightful comments throughout this work.

econometric estimates, economic theory and the modeller's subjective judgement, and a point estimate of the welfare change is calculated.

While there are many risk issues relating to a research project when eliciting the research-related parameters for the model (Alston, Norton and Pardey 1995, p. 366), the focus of this article is on the robustness of the estimated research benefits with respect to uncertainty about the values of the market parameters. Australian farmers pay levies which can be used to finance research into new production or processing technologies. Mullen, Alston and Wohlgenant (1989) (MAW), taking the particular case of the world wool top market, found that, while Australian woolgrowers received benefits from processing research, their share of the benefits from traditional production research was much larger. While MAW did some rudimentary sensitivity analysis, the extent to which their findings were dependent on the particular set of market parameters they chose was not clear. Our objective in this article is to develop a more formal probability-based approach to sensitivity analysis and to demonstrate its usefulness by revisiting the MAW findings.

In section 2, we outline the stochastic approach to sensitivity analysis that we promote in this article. In section 3, we assign a base probability specification of subjective truncated normal distributions, that centres on the MAW parameter values and has correlation among some market parameters, and report the simulated distributions for the research benefits. Because the base distributions represent a particular opinion on the parameter values, other individuals with other opinions may not relate to the simulated research-benefit distributions. To account for this, in section 4 we specify hierarchical distributions to allow for the uncertainty in specification of the subjective distributions on the parameters. The hierarchical specification attempts to cover a variety of views on the most likely value for each parameter, and/or the variation around it, by embedding a uniform distribution for the mode, and/or standard deviation, within the parent distribution of the parameter itself. In section 5, we estimate quadratic response surfaces that describe the relationships between the welfare measures and the parameters. Using these response surfaces, the sensitivity of the EDM results to variation in individual parameter values is studied by defining and calculating a sensitivity elasticity for each welfare measure with respect to each parameter. These sensitivity elasticities indicate where research effort should be expended in attempting to be more certain about individual parameters. Conclusions are given in the final section.

2. A simulation approach to sensitivity analysis

A common approach to uncertainty about parameter values has been to undertake traditional sensitivity analysis (Piggott 1992; Alston *et al.* 1995,

p. 369). A review of the theoretical and methodological issues in sensitivity analysis in agricultural economics modelling can be found in Pannell (1997). However, when a model involves more than a few uncertain parameters, an extensive nonstochastic sensitivity analysis can become unmanageable. Also, a nonstochastic sensitivity analysis does not quantify the likelihood of deviations from what are considered to be most likely parameter values. An alternative but more feasible and rigorous method for expressing uncertainty in the parameters is through a subjective probability distribution as is typically used in Bayesian inference. Modern Bayesian inference in econometrics is reviewed by Geweke (1999). Such a subjective distribution for the parameters can be formed from prior information (which is the approach adopted here) such as published econometric estimates, expert surveys or the modeller's subjective judgement. Any restrictions or theoretically required correlations among parameters can also be imposed through the prior. Alternatively, a subjective distribution could be posterior and formed after revising the prior with current sample data using an econometric model.

The advantage of using a subjective probability distribution for the uncertain parameters is that the implied probability distribution for the welfare changes can easily be found via simulation. From that distribution, various probabilities can be calculated that represent the levels of confidence about the estimated research benefits and the resulting policy recommendations. In particular, the probability of a policy variable exceeding a break-even point, which would result in a different policy recommendation, can be calculated. For example, the probability that farmers receive a larger share of the total benefits from a research investment than their share of research levy can be calculated. The approach can be viewed as a generalisation of that where a single value of welfare change is calculated from a single set of parameters. When a researcher calculates a welfare change from a single set of parameters, he or she is implicitly or explicitly using the most likely values or expected values or medians from a subjective probability distribution with zero standard deviation. Specification of the complete subjective probability distribution and calculation of the corresponding probability distribution of the resulting research benefits are therefore a more general and complete approach. Tulpule *et al.* (1992) and Scobie and Jacobsen (1992) are examples of studies which have used a similar approach.

After completing an earlier version of this paper (Zhao *et al.* 1998), we became aware of a paper by Davis and Espinoza (1998). They advocate the same general approach as we do, but we extend their work in several important ways. We examine probability distributions for welfare changes among various wool industry sectors, while they look at the sensitivity of changes in farm-retail price ratios. In terms of the methodology we promote, we accommodate a broad range of prior views on parameters by using hierarchical distributions and we introduce a mean sensitivity elasticity as a general measure of the importance of having more precise information about a parameter. Thus we follow ideas expressed in previous papers but expand them in several ways. Also, our methodology does not require Davis and Espinoza's (1998) gross approximations that were highlighted by Griffiths and Zhao (2000).

3. A base specification of parameter distributions

In MAW, the world wool top industry was modelled as using Australian raw wool (X_1 at price W_1), raw wool from other competing countries (X_2 at price W_2) and top processing inputs (X_3 at price W_3) to produce wool top (Y at price P) (MAW equations 1–8). When the adoption of a new technology causes a small shift in a supply or demand function from the initial equilibrium, the price and quantity changes for all the input and output variables can be solved in relative change form (MAW equations 9–16). Changes in economic surplus are then calculated using standard formulae. Four research scenarios were considered in MAW's base run.

3.1 Base probability distributions for the parameters

There are ten market-related parameters in the MAW model. The three input shares κ_i ($i = 1, 2, 3$) were calculated exactly after setting the initial price and quantity levels for the time period modelled. The other seven parameters are price elasticities which MAW selected 'on the basis of the theory of derived demand and after reviewing past studies of supply and demand conditions in the world wool industry' (MAW 1989, p. 35). The values were chosen for a medium run situation (ibid., p. 43). The difficulty in having to choose one value for each parameter given the limited information available about each is obvious. A natural question is how robust the estimated research benefits are to errors in the parameter values. MAW considered two scenarios of limited input substitution and a shorter displacement period by varying some of the parameter values. This variation gave a limited picture of the sensitivity of estimated research returns, but not a complete representation of the effects of parameter uncertainty.

In the following, probability distributions are assigned to the seven elasticity parameters which specify the possible values of each parameter and the corresponding probabilities. Assigning a type of probability distribution is subjective and hence must be arbitrary to some extent. We choose to use the truncated normal distribution in the base simulation. Relative to, say, triangular or uniform distributions, it represents a subjective view that a parameter has a higher probability of taking values around a most likely value, i.e. the mode, and lower possibility of taking values far away from the mode.

A truncated normal distribution is a normal distribution with values of the random variable restricted within a certain range. It is often used to impose sign or other theoretical restrictions on parameters (Griffiths 1988). For example, we may believe that the most likely value for an input substitution elasticity, σ_{ij}, is 0.1, but it could be as large as 0.5 although with a smaller chance. If we use a symmetric normal distribution, say $N(0.1, 0.2^2)$, it allows the parameter to be greater than 0.5 with 2.5 per cent probability. However, it also allows the parameter to be negative with a probability of about 30 per cent. In this case, we truncate the distribution at its left tail by restricting the parameter to be positive. The asymmetric truncated version, $N(0.1, 0.2^2|\sigma_{ij} > 0)$, serves the purpose.

Typically, a normal distribution is specified by a mean/mode, μ, and a standard deviation (SD), σ. When we truncate it, the mean is no longer equal to μ and the SD is no longer equal to σ. However, the truncations we employ here are usually well into the tails and change these values little. Consequently, for convenience we still refer to μ and σ as the mean/mode and the SD, respectively.

For comparison with MAW's results, the base distributions are set with MAW's base run parameter values as the means. The SDs are chosen after another detailed review of the published estimates, as referenced below for each of the individual parameters. These SDs could have been calculated from the actual published values, but they vary widely in terms of several important attributes — data period covered by the estimate, estimation technique, model specification. In setting reasonable SDs, we weighted heavily those estimates based on recent data and well-specified models. Most of the relevant estimates fell within the 68 per cent probability interval for each parameter. For convenience, in each case we choose to specify σ as a certain percentage of the mean μ, or as the coefficient of variation, CV (where CV $= \sigma/\mu$). Sign restrictions and correlations among parameters are imposed with truncated distributions and conditional distributions.

The demand elasticity for wool top (η) was set as -1.0 by MAW. As they noted, the published estimates for wool demand elasticity were mostly for raw wool and at the retail level, and many were for individual countries. However, they can be used as reference points when choosing the range of elasticity values for wool top demand. For example, the published raw wool demand elasticities with annual data summarised in MAW (table 1) are mostly between -0.3 and -1.6. Hill, Piggott and Griffith (1995) also reviewed some of the more recent estimates of elasticities for raw and retail wool demand for various countries. They were all inelastic. Watson (1994) discussed some different views about the wool demand elasticity and pointed out some problems with empirical estimates of this parameter. In light of this information, a CV of 20 per cent is chosen for the normal distribution. This is equivalent to assuming a 68 per cent probability that η lies between -0.8 and -1.2, and a 95 per cent probability for values between -0.6 and -1.4. The base probability distribution for η thus becomes:

$$\eta \sim N(-1, 0.2^2 | \eta < 0). \tag{1}$$

The published estimates for the substitution elasticity for wool from different countries (σ_{12}) are between 0.6 and 1.68 (MAW 1989, p. 36), although it could be argued that wool of the same type from different countries should be very good substitutes. Another point to consider is that the wool inputs from the two sources in the MAW model are similar types of raw wool that are suitable for top making. So the substitution elasticity between the two cannot be very low. Given the very limited empirical studies and very different views on this parameter, a 40 per cent CV is assigned to MAW's base value of 5. This gives the following distribution for the substitution elasticity between Australian wool and wool from competing countries:

$$\sigma_{12} \sim N(5, 2^2 | \sigma_{12} > 0). \tag{2}$$

The elasticities of substitution between wool and other processing inputs (σ_{13} and σ_{23}) were assumed to be 0.1 in MAW. No empirical estimates are available for this parameter. A 50 per cent coefficient of variation is assumed in the base specification which we hope will cover most of the possible values of this parameter. Technical substitutability between Australian wool and processing inputs, σ_{13}, and between wool from other countries and processing inputs, σ_{23}, should be similar. Even if different individuals may have very different views on the substitutability between wool input and processing inputs, the same individual would likely choose similar values for both σ_{13} and σ_{23}. This fact is accommodated by making the distribution for σ_{23} conditional on σ_{13}:

$$\sigma_{13} \sim N(0.1, 0.05^2 | \sigma_{12} > 0) \tag{3}$$

and

$$\sigma_{23} \sim N(\sigma_{13}, 0.01^2 | \sigma_{23} > 0). \tag{4}$$

A raw wool supply elasticity of 1.0 was used in MAW's base run for both Australian wool (ε_1) and competitors' wool (ε_2). It was argued that it was difficult to assign different supply elasticities to wool from different countries on either *a priori* or empirical grounds (MAW 1989, pp. 38–9). A CV of 0.2 is selected for the distribution of the Australian wool supply elasticity. The supply elasticity for wool from other countries is centred at the

Australian elasticity and is allowed to deviate only a small amount from it. The distributions for wool supply elasticities are:

$$\varepsilon_1 \sim N(1, 0.2^2|\varepsilon_1 > 0) \tag{5}$$

and

$$\varepsilon_2 \sim N(\varepsilon_1, 0.05^2|\varepsilon_2 > 0). \tag{6}$$

Finally, the supply elasticity for other processing inputs (ε_3) was assumed to have a value of 20 in MAW, given the common belief that it is almost perfectly elastic. A CV of 20 per cent is set for the normal distribution, which gives the following distribution for ε_3:

$$\varepsilon_3 \sim N(20, 4^2|\varepsilon_3 > 0). \tag{7}$$

3.2 Results for the base distributions

When all the seven parameters are allowed to change according to the probability distributions specified above, the distributions of the resulting surplus changes can be obtained through Monte Carlo simulation.[1] In the simulation, 5 000 sets of parameter values are randomly and independently sampled from the base distributions in equations 1–7. For the conditional distribution for σ_{23} in equation 4, σ_{23} is drawn from the Normal distribution using σ_{13}, drawn from equation 3, as the mean. ε_2 is drawn similarly. For any one research scenario, the EDM is then run 5 000 times with each run using a different set of parameter values. The 5 000 generated price and quantity changes imply 5 000 surplus changes, which can be used to estimate the probability distributions of the surplus changes and characteristics of these probability distributions.[2] Figure 1 shows the graphs of the probability density functions of the total surplus change and its four components resulting from Australian farm research ($ET_1 = -0.01$). We observe that the welfare changes going to Australian woolgrowers will almost certainly lie between A\$8m and A\$16m; that going to other woolgrowers will lie between – A\$5m and A\$1m; that going to top processors will lie between A\$0.05m and A\$0.25m; that going to top consumers will lie between A\$7m and A\$16m; and the total change in welfare will lie between A\$21.28m and A\$21.33m. Thus, while there is considerable uncertainty about the benefits that will accrue to the various industry groups, there is almost no uncertainty

[1] A SHAZAM instruction file is available from the senior author on request.

[2] All welfare changes are conditional on the assumption that the underlying model is correct and only the prescribed changes are occurring.

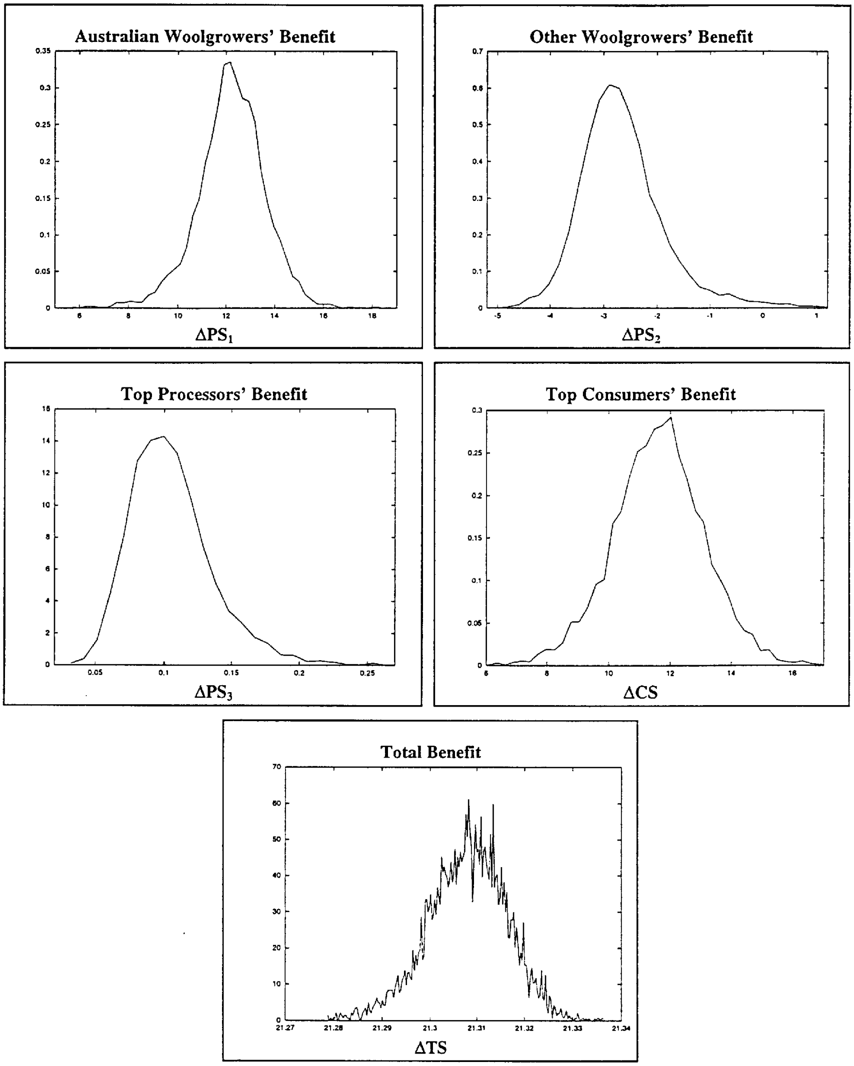

Figure 1 Probability density functions of economic surplus changes (A\$m) from Australian farm research ($ET_1 = -0.01$) — base distributions

about the change in total benefits.[3] The jagged nature of some of the distributions is typical of unsmoothed density estimates obtained by joining the midpoints of histogram classes. This is particularly so for the total benefit

[3] It can be shown analytically that the market parameters affect total welfare change ΔTS at $O(\lambda^2)$ level, but the four individual components at $O(\lambda)$ level, where λ is the small exogenous percentage change. For related details, see Zhao, Mullen and Griffith (1997).

because a large number of classes were defined over a relatively narrow interval. Figures for the other three research scenarios can be obtained similarly but are not presented to conserve space.

We can also calculate some summary statistics and probability intervals from the simulation data and these are summarised in table 1. The columns represent the four research scenarios considered by MAW in their table 3, Part A (1989, p. 40). The rows represent the total benefit and its four components for each research scenario. Within each row are reported the MAW point estimates, and the means, SDs, CVs and 95 per cent probability intervals (PIs) from the simulation data. The interval endpoints are given by the 0.025 and 0.975 empirical quantiles. A 95 per cent PI represents the range of values for a research benefit for which we have 95 per cent confidence, given our beliefs on the possible parameter values specified in the prior distributions. Because it is derived from subjective prior distributions, it is different from a conventional sampling theory confidence interval. Asymmetry in a distribution can be detected by comparing the 95 per cent interval with approximately two standard deviations from the mean. The figures in parentheses are the percentage shares of the total industry benefits accruing to the different groups.

For example, the cell for the ΔPS_1 row and the $ET_1 = -0.01$ column gives summary statistics for the distribution in the first segment of figure 1. The mean of ΔPS_1 from this research scenario is A\$12.20m and the average share of the total benefits is 57.3 per cent. These values are very close to the MAW point estimates of A\$12.38m and 58.1 per cent, respectively. The SD from the simulation data is A\$1.39m which implies a CV for the actual benefit of 0.11. The SD also implies a variation of 6.5 percentage points around the Australian woolgrowers' share of benefits of 57.3 per cent. Finally, the 95 per cent PI is from A\$9.24m to A\$15.82m, or alternatively, we have 95 per cent confidence that Australian woolgrowers' share of the benefits from this research scenario will lie between 43.4 per cent and 69.5 per cent.

Several things can be observed from table 1. First, the differences between the means of the distributions of surplus changes and the corresponding MAW point estimates of surplus changes are very small. This result is not necessarily expected because of the implicit nonlinear relationship between the surplus measures and the parameters.[4]

[4] $S(E(\Theta)) \neq E(S(\Theta))$ when $S(\Theta)$ is nonlinear, where $S(\Theta)$ represents the surplus measure as a function of the parameter values, $E(.)$ is the mean of random variable (.), $E(S(\Theta))$ is the mean of the distribution for surplus measure and $S(E(\Theta)) = \text{MAW}$ is the surplus for the mean of the parameter Θ which equals the MAW point estimates.

Table 1 Summary statistics for research benefits and shares of total benefits using the base distributions for parameters ($n = 5\,000$) (A$m)

	$EN = 0.005$ Textile Research	$ET_1 = -0.01$ Aust. Farm Research	$ET_3 = -0.01$ Processing Research	$ET_1 = -.01$; $ET_2 = -.005$ Farm Research Adoption
ΔPS_1: Aust. Woolgrowers				
MAW	5.82 (27.3%) [a]	12.38 (58.1%)	2.08 (24.4%)	10.97 (39.6%)
Mean	5.82 (27.4%)	12.20 (57.3%)	2.076 (24.4%)	10.89 (39.3%)
SD	0.94 (4.4%)	1.39 (6.5%)	0.39 (4.6%)	1.38 (5.0%)
CV [b]	0.16	0.11	0.19	0.13
95% PI [c]	(3.99, 8.45) ((18.7%, 36.2%))	(9.24, 15.82) ((43.4%, 69.5%))	(1.30, 3.17) ((15.3%, 33.5%))	(8.24, 14.82) ((29.8%, 49.4%))
ΔPS_2: Other Woolgrowers				
MAW	3.49 (16.4%)	−2.80 (−13.1%)	1.25 (14.7%)	1.46 (5.3%)
Mean	3.493 (16.4%)	−2.62 (−12.3%)	1.246 (14.6%)	1.56 (5.6%)
SD	0.57 (2.7%)	0.90 (4.2%)	0.24 (2.8%)	0.77 (2.8%)
CV	0.16	−0.35	0.19	0.49
95% PI	(2.40, 5.07) ((11.3%, 21.8%))	(−3.95, 1.73) ((−18.6%, −1.9%))	(0.78, 1.91) ((9.2%, 20.1%))	(0.13, 4.06) ((0.5%, 11.3%))
ΔPS_3: Top Processors				
MAW	0.13 (0.6%)	0.10 (0.5%)	0.09 (1.1%)	0.14 (0.5%)
Mean	0.130 (0.6%)	0.106 (0.5%)	0.091 (1.1%)	0.138 (0.5%)
SD	0.037 (0.2%)	0.03 (0.15%)	0.03 (0.4%)	0.04 (0.15%)
CV	0.28	0.30	0.34	0.30
95% PI	(0.08, 0.26) ((0.4%, 1.0%))	(0.058, 0.22) ((0.3%, 0.8%))	(0.045, 0.20) ((0.5%, 1.9%))	(0.076, 0.29) ((0.28%, 0.85%))
ΔCS: Top Consumers				
MAW	11.85 (55.7%)	11.63 (54.5%)	5.09 (59.8%)	15.13 (54.6%)
Mean	11.84 (55.6%)	11.616 (54.5%)	5.094 (59.9%)	15.10 (54.6%)
SD	1.51 (7.1%)	1.51 (7.1%)	0.63 (7.4%)	1.96 (7.1%)
CV	0.13	0.13	0.12	0.13
95% PI	(8.82, 15.89) ((41.4%, 69.5%))	(8.59, 15.62) ((40.3%, 74.5%))	(3.85, 6.81) ((45.2%, 80.0%))	(11.12, 20.41) ((40.2%, 68.4%))
ΔTS: Total Benefit				
MAW	21.28	21.31	8.51	27.69
Mean	21.284	21.307	8.506	27.684
SD	0.009	0.021	0.019	0.038
CV	0.0004	0.001	0.002	0.001
95% PI	(21.275, 21.295)	(21.289, 21.328)	(8.505, 8.508)	(27.669, 27.706)

Notes:
[a] Figures in brackets are the percentage shares of total benefits going to the various industry groups.
[b] CV represents the coefficient of variation which is the ratio of standard deviation to mean.
[c] The 95 per cent probability intervals are ranges of benefits and percentage shares (in brackets) with 95% probability.

Second, in line with figure 1, the very small standard deviations for ΔTS show that the simulated total surplus changes (ΔTS) vary very little. Presumably, total benefits are more responsive to the input cost shares, the amounts of research-induced supply/demand shifts and where the research occurs.

Third, the CVs for the surplus changes are generally less than the CVs of 20–50 per cent in the base parameter distributions for all four research scenarios. They are less than 20 per cent for both Australian woolgrowers' gains (ΔPS_1) and top consumers' gains (ΔCS) and mostly less than 35 per cent for top processors' gains (ΔPS_3) and other woolgrowers' gains (ΔPS_2).

Fourth, one of the major conclusions in the MAW study is that 'on-farm' research (ET_1) gives a greater share of the total benefit to Australian woolgrowers ($\Delta PS_1/\Delta TS$) than 'off-farm' research (EN or ET_3). Looking at the first row of table 1, especially the probability intervals for benefit shares, we see that there is no overlap between the PI for $\Delta PS_1/\Delta TS$ for the ET_1 scenario with those for the EN and ET_3 scenarios. So it seems that there is little chance for off-farm research to be more beneficial than farm research for Australian woolgrowers. Probabilities such as these can be quantified by counting the proportion of times the difference in benefit shares lies within a specified interval. In this case, we find that

$$P(0.25 < (\Delta PS_1/\Delta TS|ET_1) - (\Delta PS_1/\Delta TS|EN) < 0.82) = 100\% \qquad (8)$$

and

$$P(0.03 < (\Delta PS_1/\Delta TS|ET_1) - (\Delta PS_1/\Delta TS|ET_3) < 0.47) = 100\% \qquad (9)$$

That is, Australian woolgrowers will always receive a larger share of the total benefit from Australian farm research than they do from the two types of processing research (25 per cent to 82 per cent more, and 3 per cent to 47 per cent more, respectively). In other words, given the large variation of the parameters specified in the base distributions, MAW's conclusion, that farm research is more beneficial for Australian woolgrowers, is remarkably robust. Perhaps this result is true for all parameter values; an analytical investigation might be a fruitful future endeavour.

4. Hierarchical distributions for the parameters

In this section, hierarchical distributions are specified, and results for the hierarchical simulations presented.

4.1 Hierarchical probability specification

The distributions for the estimated research benefits derived in section 3 are generated from a base probability specification for the parameters, which represents MAW's view on the most likely values for the parameters and our view, after considering the published empirical estimates, on their possible variation around the MAW values. However, other researchers may not agree with the particular distributions we have given in the base specification. There are two ways of responding to this criticism. On the one hand, we can argue that at least our base-distribution specification is more general than that of MAW, who bet on one particular value for a parameter with 100 per cent certainty. Our approach demonstrates a method of deriving a probability distribution for the research benefits as long as we can quantify our uncertainty about the parameter values with subjective distributions. The procedure can be repeated using any other individual's parameter specifications.

On the other hand, hierarchical distributions for the parameters can be specified to account for the uncertainty about the specification of the subjective distributions. A hierarchical distribution allows for different views on both the most likely value for a parameter (mode/mean) and the possible variation around it (SD). The mode/mean and SD for a distribution are allowed to vary by being assigned their own probability distributions within the parent distribution for the parameter. The effect of more diverse views about the parameters on the uncertainty about the research benefits can thus be analysed. Ideally, a survey of expert opinions can be conducted to obtain information on the range of possible views about a particular parameter.

In the following, a uniform distribution is assigned to the mode of the truncated normal distribution to account for different opinions on the most likely value for a parameter. The range of the uniform distribution is chosen, after considering the past empirical estimates, to be wide enough to cover most of the possible values for a parameter. Given the wide variation permitted in the mode, less variation was needed for the truncated normal distributions. A fixed CV of 0.1 was used. This gives the following specifications for the seven hierarchical distributions:

$$\text{(a) } \overline{\eta} \sim U(-2.0, -0.3), \qquad \text{(b) } \eta \sim N(\overline{\eta}, (0.1\overline{\eta})^2 | \eta < 0); \tag{10}$$

$$\text{(a) } \overline{\sigma}_{12} \sim U(2, 5), \qquad \text{(b) } \sigma_{12} \sim N(\overline{\sigma}_{12}, (0.1\overline{\sigma}_{12})^2 | \sigma_{12} > 0); \tag{11}$$

$$\text{(a) } \overline{\sigma}_{13} \sim U(0, 1), \qquad \text{(b) } \sigma_{13} \sim N(\overline{\sigma}_{13}, (0.1\overline{\sigma}_{13})^2 | \sigma_{13} > 0); \tag{12}$$

$$\text{(a) } \overline{\sigma}_{23} = \sigma_{13}, \qquad \text{(b) } \sigma_{23} \sim N(\overline{\sigma}_{23}, 0.01^2 | \sigma_{23} > 0); \tag{13}$$

$$\text{(a) } \overline{\varepsilon}_1 \sim U(0.2, 2.0), \qquad \text{(b) } \varepsilon_1 \sim N(\overline{\varepsilon}_1, (0.1\overline{\varepsilon}_1)^2 | \varepsilon_1 > 0); \tag{14}$$

$$\text{(a) } \overline{\varepsilon}_2 = \varepsilon_1, \qquad \text{(b) } \varepsilon_2 \sim N(\overline{\varepsilon}_2, 0.05^2 | \varepsilon_2 > 0); \tag{15}$$

$$\text{(a) } \overline{\varepsilon}_3 \sim U(2, 30), \qquad \text{(b) } \varepsilon_3 \sim N(\overline{\varepsilon}_3, (0.1\overline{\varepsilon}_3)^2 | \varepsilon_3 > 0). \tag{16}$$

Of particular interest is the input substitution elasticity between wool and processing inputs (σ_{13}, σ_{23}) that we have allowed to be between zero and one. This is a significant increase from the MAW value of 0.1. A more recent empirical study by Wohlgenant (1989) for various US farm products revealed values as big as 0.96 (table 3, p. 250), which suggested that this elasticity could be larger than previously thought. By allowing the range of zero to one, we take into account the two extreme views on the value of this parameter and study the effect of these views on the results.

4.2 Results for the hierarchical distributions

Given the wide range allowed for the parameter values and the hierarchical nature of the distributions, a sample size of 10 000 is used for the hierarchical simulation. To obtain each draw of the 10 000 observations, the modes are first drawn from the uniform distributions in the (a)s of equations 10–16. The SDs are calculated as 10 per cent of the modes where applicable, and the parameter values are then drawn from the truncated normal distributions in the associated (b)s. The EDM is then solved using the chosen set of parameters and the five surplus measures are calculated for the four research scenarios.

Graphs of the probability density functions for the five surplus measures resulting from Australian farm research ($ET_1 = -0.01$) based on the hierarchical parameter distributions are shown in figure 2. The corresponding curves from figure 1 are superimposed on figure 2 for comparison, and the scales on the horizontal axes are changed slightly. The impact of the additional uncertainty specified through the hierarchical distributions is readily observed. Naturally, because we allow for a wider range of parameter values in the hierarchical specification, the variation of the research benefits is larger than that in the base distribution. Uncertainty about the benefits to top processors (ΔPS_3), Australian woolgrowers (ΔPS_1) and top consumers (ΔCS) is significantly increased; for other woolgrowers' benefits (ΔPS_2), the range has changed very little, but the centre of the distribution has shifted noticeably to the right. Also, there is now a non-zero probability that the benefits to top processors (ΔPS_3) will be negative.

A summary of the simulation results is given in table 2. The differences between the MAW estimates and the mean values of the welfare distributions are greater in table 2 than those in table 1. This is because the hierarchical distributions are not centred on the MAW parameter values. A comparison of the benefits to Australian woolgrowers suggests that the expected benefit from processing research in particular has fallen markedly and is now much more uncertain. There continues to be relatively little

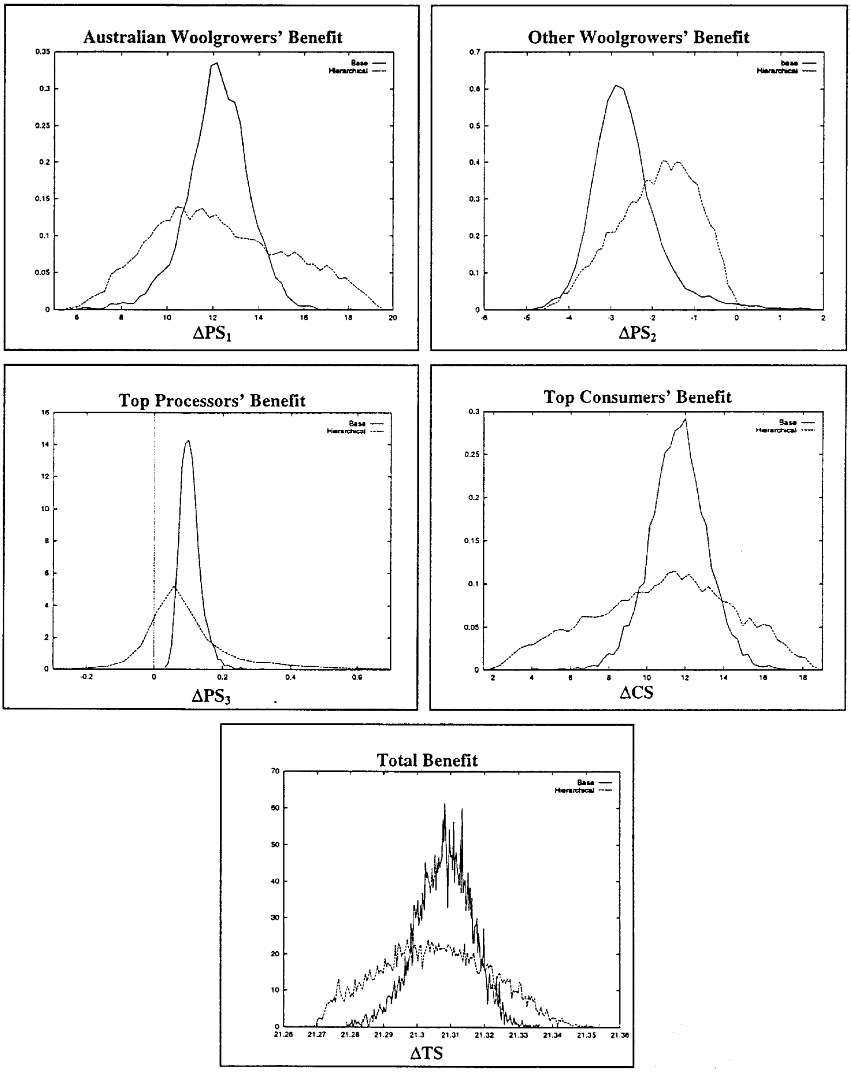

Figure 2 Probability density functions of economic surplus changes (A\$m) from Australian farm research ($ET_1 = -0.01$) — hierarchical vs. base distributions

uncertainty about total benefits despite considerable uncertainty about how this total is distributed among its components.

Let us examine again the Australian woolgrowers' benefit share ($\Delta PS_1/\Delta TS$) from Australian farm research (ET_1) versus processing research (EN and ET_3). Looking at the first row in table 2 and the corresponding density functions in figure 3, there appears to be a chance for processing research to generate a greater share of benefits to Australian woolgrowers

Table 2 Summary statistics for research benefits and shares of the total benefits using hierarchical distributions for parameters ($n = 10\,000$) (A\$m)

	$EN = 0.005$ Textile Research	$ET_1 = -0.01$ Aust. Farm Research	$ET_3 = -0.01$ Processing Research	$ET_1 = -.01$; $ET_2 = -.005$ Farm Research Adoption
ΔPS_1:				
Aust. Woolgrowers				
MAW	5.82 (27.3%) [a]	12.38 (58.1%)	2.08 (24.4%)	10.97 (39.6%)
Mean	5.81 (27.3%)	11.36 (58.0%)	1.17 (13.8%)	11.41 (41.2%)
SD	2.16 (10.1%)	2.93 (13.8%)	1.15 (13.6%)	3.23 (11.7%)
CV [b]	0.37	0.24	0.98	0.28
95% PI [c]	(2.02, 10.11)	(7.43, 18.17)	(−1.13, 3.41)	(5.86, 17.84))
	((9.5%, 47.5%))	((34.9%, 85.4%))	((−13.3%, 40.1%))	((21.2%, 64.5%))
ΔPS_2:				
Other Woolgrowers				
MAW	3.49 (16.4%)	−2.80 (−13.1%)	1.25 (14.7%)	1.46 (5.3%)
Mean	3.48 (16.4%)	−1.90 (−8.9%)	0.70 (8.3%)	2.18 (7.9%)
SD	1.30 (6.1%)	0.95 (4.5%)	0.69 (8.1%)	1.46 (5.3%)
CV	0.37	−0.50	0.98	0.67
95% PI	(1.21, 6.06)	(−3.85, −0.33)	(−0.68, 2.04)	(−0.52, 4.96)
	((5.7%, 28.5%))	((−18.1%, −1.5%))	((−8.0%, 24.0%))	((−1.9%, 17.9%))
ΔPS_3:				
Top Processors				
MAW	0.13 (0.6%)	0.10 (0.5%)	0.09 (1.1%)	0.14 (0.5%)
Mean	0.30 (1.4%)	0.11 (0.5%)	0.43 (5.0%)	0.14 (0.5%)
SD	0.26 (1.2%)	0.16 (0.8%)	0.40 (4.7%)	0.21 (0.8%)
CV	0.88	1.51	0.94	1.51
95% PI	(0.006, 1.07)	(−0.009, 0.55)	(0.006, 1.63)	(−0.12, 0.72)
	((0.3%, 5.1%))	((−0.4%, 2.6%))	((0.6%, 19.2%))	((−0.4%, 2.6%))
ΔCS:				
Top Consumers				
MAW	11.85 (55.7%)	11.63 (54.5%)	5.09 (59.8%)	15.13 (54.6%)
Mean	11.69 (54.9%)	10.73 (50.4%)	6.20 (72.9%)	13.96 (50.4%)
SD	3.49 (16.4%)	3.59 (16.8%)	1.80 (21.1%)	4.66 (16.8%)
CV	0.30	0.33	0.29	0.33
95% PI	(4.84, 17.87)	(3.66, 17.04)	(2.86, 9.90)	(4.79, 22.17)
	((22.7%, 84.0%))	((17.2%, 80.0%))	((33.6%, 116.3%))	((17.3%, 80.1%))
ΔTS:				
Total Benefit				
MAW	21.28	21.31	8.51	27.69
Mean	21.284	21.30	8.508	27.686
SD	0.014	0.022	0.013	0.026
CV	0.0006	0.001	0.002	0.001
95% PI	(21.27, 21.31)	(21.27, 21.34)	(8.504, 8.510)	(27.65, 27.73)

Notes:
[a] Figures in brackets are the percentage shares of total benefits going to the various industry groups.
[b] CV represents the coefficient of variation which is the ratio of standard deviation to mean.
[c] The 95 per cent probability intervals are ranges of benefits and percentage shares (in brackets) with 95% probability.

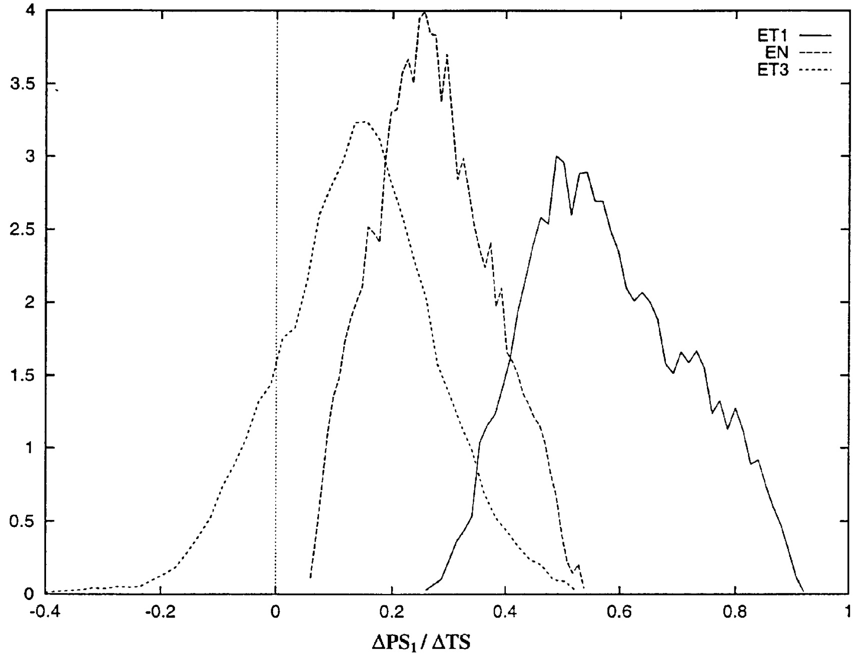

Figure 3 Probability density functions of Australian woolgrowers' benefit shares ($\Delta PS_1/\Delta TS$) from various research (ET_1: Farm Research, EN: Textile Research, and ET_3: Top Processing Research)

than that from farm research. Both the 95 per cent probability intervals and the distribution densities overlap. However, examining only the marginal distributions of the surplus changes, rather than the joint distribution, ignores correlation between the surplus changes. When we look at the simulation data to calculate the probability, it turns out that the parameter values that give larger values of $\Delta PS_1(EN$ and $ET_3)$ also produce larger values of $\Delta PS_1(ET_1)$. As a result, it is calculated that

$$P(0.16 < (\Delta PS_1/\Delta TS|ET_1) - (\Delta PS_1/\Delta TS|EN) < 0.54) = 100\% \qquad (17)$$

and

$$P(0.16 < (\Delta PS_1/\Delta TS|ET_1) - (\Delta PS_1/\Delta TS|ET_3) < 1.25) = 100\% \qquad (18)$$

That is, Australian woolgrowers will always receive at least 16 per cent more of the total benefit from Australian farm research than they do from the two types of processing research. This is an interesting result because it may imply that even when we increase the range of the possible values for the parameters, which may result in an even larger overlap of the distributions of $\Delta PS_1/\Delta TS(ET_1)$ and $\Delta PS_1/\Delta TS(EN$ or $ET_3)$ than that observed here,

$\Delta PS_1/\Delta TS(ET_1)$ may never be smaller than $\Delta PS_1/\Delta TS(EN$ or $ET_3)$ because of common dependency on the parameter values.

Much of the attention in the EDM literature regarding sensitivity to parameter values has been on the input substitution elasticity (for example, Alston and Scobie 1983; Holloway 1989; Mullen, Wohlgenant and Farris 1988). When the input substitution elasticity (σ_{ij}) is allowed to be greater than zero, the shares of the total research benefits to producers and processors will be dependent on where the research occurs. Also, when σ_{ij} is allowed to be greater than the output demand elasticity (η), the provider of input X_i will lose from research in the production of X_j (Holloway 1989). Since we do allow for the possibility that the input substitution elasticity may be larger than the output demand elasticity in the hierarchical distribution, there is a chance that farm input suppliers (ΔPS_1) can lose from top processing research (ET_3), and, symmetrically, that top processors (ΔPS_3) can lose from farm research (ET_1). Given the parameter uncertainty specified in the hierarchical distributions, the probability of these situations occurring can be calculated as:

$$P(\Delta PS_1(ET_3) < 0) = P(\Delta PS_3(ET_1) < 0) = P(|\eta| < \sigma_{13}) = 15\% \tag{19}$$

In other words, there is a 15 per cent chance that Australian woolgrowers can lose from research dollars invested in the top processing sector.

5. Response surface and sensitivity to individual parameters

In this section, we estimate quadratic response surfaces describing the relationships between the welfare measures and the parameters, and examine the sensitivity of the EDM results to variations in individual parameters.

5.1 Response surface

The simulation study defines a relationship between a particular welfare measure S and a set of parameters $\Theta = (\theta_1, \theta_2, \ldots, \theta_n)$, which can be written in general as:

$$S = S(\Theta) = f(\theta_1, \theta_2, \ldots, \theta_j, \ldots, \theta_n) \tag{20}$$

It is this relationship that was used to numerically estimate the probability density function for S from the joint probability density function for Θ (as shown in figures 1 and 2). In this section, we define a measure of the sensitivity of S to changes in a particular parameter θ_j. This measure depends not only on the responsiveness of S to θ_j but also on probable variations in the parameters θ_j ($j = 1, \ldots, n$).

In general, functions like equation 20 are often complicated and analytically unavailable. For the case of the MAW model, the welfare changes are quadratic functions of price and quantity changes, which are calculated by multiplying the inverse of an 8 by 8 parameter matrix by an 8 by 4 parameter matrix, by an exogenous shifter matrix. The resulting relationship between each of the welfare changes and the seven market-related parameters is laborious to derive analytically.

Given the complicated nature of the relationship and the large number of simulated observations that reflect the relationship, it is reasonable to try to estimate it with its second order approximation, i.e., a quadratic function. Such an estimated function is frequently called a response surface in the simulation literature. The response surfaces to be estimated are

$$S_k = \alpha_0 + \sum_{i=1}^{7} \alpha_i \theta_i + \sum_{i=1}^{7} \beta_i \theta_i^2 + \sum_{\substack{i,j=1 \\ i<j}}^{7} \gamma_{ij} \theta_i \theta_j + e_k \qquad (k = 1, \ldots, 5), \tag{21}$$

where S_k $(k = 1, \ldots, 5)$ represent the five welfare changes, θ_i $(i = 1, \ldots, 7)$ represent the seven market-related parameters, α_0, α_i, β_i and γ_{ij} $(i, j = 1, \ldots, 7)$ are coefficients to be estimated, and $e_k (k = 1, \ldots, 5)$ are error terms.

For each of the four research scenarios, the five equations in 21 are estimated using the 10 000 observations drawn from the hierarchical distributions. Details of the estimated coefficients are not presented. The R^2's for the regressions are all very high (most are greater than 0.98) except for the total benefit (ΔTS), which, as we have already seen, is little affected by changes in the parameter values.

5.2 Sensitivity elasticities for individual parameters

One of the objectives of this study is to examine the sensitivity of the estimated research benefits to individual parameters. From an empirical point of view, identification of the parameters to which the results are most sensitive provides information on where careful choice is required, or if time permits, on where effort should be focused in estimation.

Given the response functions we estimate, one way to present the responsiveness of the welfare measures to individual parameters is to plot the welfare measure S_k in equation 21 against changes in one individual parameter with the other six parameters fixed, say, at the MAW values. If we graph Australian woolgrowers' benefit (ΔPS_1) from farm research (ET_1) against changes in each of the individual parameters, it can be shown that Australian woolgrowers' benefit is negatively related to Australian wool supply elasticity (ε_1) and positively related to the other six market parameters. Similar graphs can be drawn for other benefit shares and other research scenarios.

Alternatively, some kind of sensitivity index can be calculated that summarises the sensitivity of a welfare measure to individual parameters. A straightforward sensitivity index is the ratio of the percentage change of the welfare measure to the percentage change of a parameter, or, in other words, the sensitivity 'elasticity'. We could calculate this elasticity by changing an individual parameter by 1 per cent, from its MAW base value, while holding the other parameters fixed at the MAW values, and calculating the percentage change of the research benefits from the MAW point estimate. An example of this approach is the sensitivity analysis for the ABARE textile model TEXABARE (Tulpule *et al.* 1992). However, there are at least three disadvantages with this measure. First, it only measures sensitivity with respect to a single point. The sensitivity could be very different for other values of Θ away from the MAW values. Second, it only considers a 1 per cent change from the MAW value, while in practice, even if the MAW value were the true value, the possible deviation from the true value in empirical applications can be much larger. Third, this definition does not take into account the probability of a particular parameter value being true. It is simply a nonstochastic one point sensitivity analysis.

In the following, we define a sensitivity elasticity using the estimated response function and the probability density functions of the parameters, $p(\Theta)$. This sensitivity elasticity represents the 'average' sensitivity of a research benefit across all possible values of all parameters. The variation of the parameters is specified by the hierarchical distributions in equations 10–16. The possibility of a parameter value being true is also taken into account by using the probability distribution $p(\Theta)$ as a 'weight' in the average.

The sensitivity elasticity of S_k $(k = 1, \ldots, 5)$ to parameter θ_i $(i = 1, \ldots, 7)$ at any parameter point Θ is given through partial differentiation of the quadratic response functions in equation 21:

$$\begin{aligned} E_{ki} &= (\partial S_k/\partial \theta_i)(\theta_i/S_k) \\ &= \left(\alpha_i + 2\beta_i\theta_i + \sum_{\substack{j=1 \\ j\neq i}}^{7} \gamma_{ij}\theta_j\right)(\theta_i/S_k) = g_{ki}(\Theta) \quad (k = 1, \ldots, 5;\, i = 1, \ldots, 7) \end{aligned} \tag{22}$$

The sensitivity elasticity E_{ki} is a function of all parameters Θ and is therefore different at different points of Θ. When possible values of Θ and the probability of each value occurring $p(\Theta)$ are specified by the hierarchical distribution, the possible values of the sensitivity elasticity E_{ki} and the probability distribution for E_{ki} are defined. This distribution can be obtained from the simulation. In particular, the mean and SD for E_{ki} are:

$$\mathrm{Mean}(E_{ki}) = \int_{\Theta} g_{ki}(\Theta)p(\Theta)d\Theta \tag{23}$$

$$\mathrm{SD}(E_{ki}) = \left(\int_{\Theta} [g_{ki}(\Theta) - \mathrm{Mean}(g_{ki}(\Theta))]^2 p(\Theta)d\Theta\right)^{1/2} \tag{24}$$

Numerically, these quantities can be estimated using the simulation data as follows. The 10 000 observations of Θ from the hierarchical distribution are used to calculate, from equation 22, the 10 000 observations of E_{ki}. The sample mean and SD of E_{ki} are the estimates for the population mean and SD in equations 23 and 24. Results for the mean sensitivity elasticities for all four research scenarios are given in table 3. These values can be used as a guide for the sensitivity of a welfare measure to a particular parameter and thus for comparison of the relative importance of different parameters. The signs of the mean sensitivity elasticities in table 3 provide information on the direction of the relationship between each welfare measure and each parameter. Conversely, any signs that are counter-intuitive may suggest possible flaws in the model.

From table 3, a 1 per cent increase in an individual parameter only changes the total surplus by at most 0.002 per cent. Thus the total benefit is insensitive to all elasticity parameters. For all research scenarios, all four components of the total benefit are relatively sensitive to wool top demand (η) and Australian raw wool supply (ε_1) elasticities, as predicted by theory. Increasing η will increase ΔPS_1 but decrease ΔCS, while the directions of the benefit changes for other woolgrowers (ΔPS_2) and top processors (ΔPS_3) depend on the research scenarios considered. An increase in ε_1 will result in the benefit moving from Australian woolgrowers to other industry groups in all research scenarios. Only the benefit to other woolgrowers (ΔPS_2) is sensitive to other countries' wool supply elasticity (ε_2) for all four research scenarios. Input substitution between wool from the two sources (σ_{12}) only affects the two raw wool providers for the case of farm research. Input substitution elasticities between farm and processing inputs (σ_{13} and σ_{23}) seem to be important for other input suppliers. ΔPS_3 shows large percentage changes for some parameters although the change in the actual term may not be large because of the small magnitude of the benefit. In the case of processing research, σ_{13} and σ_{23} also influence benefits to other groups.

Concentrating on Australian woolgrowers' benefit (ΔPS_1) from various types of research, η and ε_1 are shown to be the most influential parameters. A 1 per cent increase in η will result in a 0.21 per cent to 0.54 per cent, on average, increase in ΔPS_1; and a 1 per cent increase in ε_1 will result in a 0.35

Table 3 Mean sensitivity elasticities of various research benefits to individual parameters resulting from various research scenarios ($n = 10\,000$)

	η	σ_{12}	σ_{13}	σ_{23}	ε_1	ε_2	ε_3
$EN = 1\%$:							
Textile Res.							
ΔPS_1	0.53	−0.004	−0.04	−0.006	−0.41	−0.066	0.002
ΔPS_2	0.53	−0.004	−0.014	−0.032	−0.15	−0.33	0.002
ΔPS_3	0.66	0.028	−0.56	0.91	0.24	−0.095	−0.27
ΔCS	−0.44	0.001	0.019	0.021	0.23	0.13	0.011
ΔTS	0.7E-3	0.8E-5	−0.1E-3	0.2E-3	0.3E-3	0.2E-3	0.2E-4
$ET_1 = -1\%$:							
Aus. Farm Res.							
ΔPS_1	0.21	0.12	0.037	−0.001	−0.41	0.047	0.002
ΔPS_2	−1.14	1.06	−0.052	−0.041	0.48	−0.36	−0.015
ΔPS_3	1.66	0.13	−3.13	1.26	1.33	−0.45	0.36
ΔCS	−0.44	0.002	−0.043	−0.006	0.56	−0.10	0.003
ΔTS	0.7E-3	0.5E-3	−0.1E-3	0.2E-3	0.8E-3	0.2E-3	−0.2E-4
$ET_3 = -1\%$:							
Proces. Res.							
ΔPS_1	0.54	0.009	0.19	−0.097	−0.35	0.015	0.13
ΔPS_2	1.91	−0.016	−0.97	−0.86	−0.15	−0.47	0.034
ΔPS_3	0.95	0.21	−0.22	1.95	−1.26	1.65	−0.42
ΔCS	−0.43	−0.001	0.14	0.097	0.11	0.048	0.027
ΔTS	0.2E-3	0.2E-4	0.2E-2	−0.2E-2	0.7E-4	0.6E-4	−0.6E-4
$ET_1 = -1\%$ and							
$ET_2 = -0.5\%$:							
Farm Res. Adoption							
ΔPS_1	0.30	0.068	0.048	0.0005	−0.41	−0.003	0.002
ΔPS_2	3.30	−1.42	0.23	0.090	−1.54	−0.41	−0.064
ΔPS_3	−2.03	0.003	−0.10	0.23	1.31	−0.11	1.66
ΔCS	−0.44	0.002	−0.039	−0.010	0.39	0.065	0.003
ΔTS	0.9E-3	0.7E-4	0.4E-3	−0.4E-3	0.8E-3	0.5E-4	−0.1E-5

per cent to 0.41 per cent decrease in ΔPS_1. ΔPS_1 is also shown to be sensitive to the input substitution elasticity between raw wool and processing inputs (σ_{13} and σ_{23}) and the supply elasticity for processing inputs (ε_3) for the scenario of top processing research (ET_3).

6. Conclusion

Uncertainty about parameter values, and hence about model results, is a common issue in any economic modelling exercise. This is especially so when using synthetic models like EDM to estimate research benefits in terms of economic surplus changes. The stochastic procedure demonstrated in this article represents the uncertainty about model results with a probability distribution that is derived from the subjective probability distribution that quantifies the modeller's uncertainty about the underlying parameter values. Various probabilities can also be calculated that represent the levels of confidence about the model estimates and resulting policy conclusions. Although the procedure can be repeated with different subjective distributions representing different individuals' views on the possible values of the parameters, a hierarchical distribution is also illustrated in order to incorporate these different views on both the most likely value and the variation around it for particular parameters. Response surfaces that describe the relationships of the welfare measures to the parameters are estimated. A sensitivity elasticity is defined and calculated from the response surfaces to summarise the sensitivity of the results to individual parameters. These sensitivity elasticities provide information on which parameters should be more precisely estimated for empirical applications of a model. Of course, conclusions will be conditional on the model that is set up.

An EDM application by Mullen *et al.* (1989) that evaluated the returns from various research scenarios for the Australian wool industry is chosen to illustrate the more formal probability-based approach to sensitivity analysis. The robustness of their major conclusions to a range of parameter values is tested. A number of important results were derived. The total research benefit was shown to be extremely robust to changes in parameter values, as is consistent from intuition, but its distribution among different industry groups was not.

Important conclusions in MAW's article were that Australian woolgrowers gain a bigger share of benefits from farm research than from processing research and that they do not lose from processing research (as is possible if substitution possibilities are large relative to the response of demand for the final product to price changes). Given the wide range of the parameter values specified in the hierarchical distribution, we found that these results were robust. Under no set of parameter values did woolgrowers receive a larger share of benefits from processing research than from production research. Further, there was only a 15 per cent probability, given the hierarchical distributions used here, for Australian woolgrowers to lose from top processing research.

Another result of MAW was that the distribution of research benefits is very sensitive to the input substitution elasticity between farm inputs and processing inputs. In this study, the estimated mean sensitivity elasticities for these two parameters were found to be relatively large for the processing research scenario, but mostly small for the farm and textile research scenarios. Thus estimated research benefits from top processing research can involve large errors if the choice of input substitution parameters is not precise. Also, lack of precise knowledge about the input substitution parameters can mean that larger percentage changes than the 1 per cent change on which our sensitivity measure is based are relevant. In this sense, knowing more about these parameters may be crucial.

To summarise, the approach demonstrated in this article provides a feasible procedure for dealing with uncertainty in parameters in economic models. Ideally, a more formalised Bayesian approach can be used to combine prior distributions, possibly elicited from surveys of expert opinions, and current sample information using econometric models to derive posterior distributions for the parameters and model outputs. However, given that data for estimation of some parameters are unavailable, or costly to obtain, the procedure we have described provides a rigorous framework for evaluating research benefits in the presence of parameter uncertainty.

References

Alston, J.M. 1991, 'Research benefits in a multimarket setting: a review', *Review of Marketing and Agricultural Economics,* vol. 59, no.1, pp. 23–52.

Alston, J.M., Norton, G.W. and Pardey, P.G. 1995, *Science Under Scarcity: Principles and Practice for Agricultural Research Evaluation and Priority Setting,* Cornell University Press, Ithaca and London.

Alston, J.M. and Scobie, G.M. 1983, 'Distribution of research gains in multistage production systems: comment', *American Journal of Agricultural Economics*, vol. 65, no. 2, pp. 353–6.

Davis, G.C. and Espinoza, M.C. 1998, 'A unified approach to sensitivity analysis in equilibrium displacement models', *American Journal of Agricultural Economics*, vol. 80, no. 4, pp. 868–79.

Freebairn, J.W., Davis, J.S. and Edwards, G.W. 1982, 'Distribution of research gains in multistage production systems', *American Journal of Agricultural Economics,* vol. 64, no. 1, pp. 39–46.

Gardner, B.L. 1975, 'The farm-retail price spread in a competitive food industry', *American Journal of Agricultural Economics,* vol. 57, no. 3, pp. 399–409.

Geweke, J. 1999, 'Using simulation methods for Bayesian econometric models: inference, development and communication', *Econometric Reviews*, vol. 18, no. 1, pp. 1–74.

Griffiths, W.E. 1988, 'Bayesian econometrics and how to get rid of those wrong signs', *Review of Marketing and Agricultural Economics,* vol. 56, no. 1, pp. 36–56.

Griffiths, W.E. and Zhao, X. 2000, 'A unified approach to sensitivity analysis in equilibrium displacement models: comment', *American Journal of Agricultural Economics,* forthcoming.

Hill, D.J., Piggott, R.R. and Griffith, G.R. 1995, *Assessing the Impacts of Incremental Wool Promotion Expenditure: An Equilibrium Displacement Modelling Approach*, technical report to the International Wool Secretariat, Department of Agricultural and Resource Economics, University of New England.

Holloway, G.J. 1989, 'Distribution of research gains in multistage production systems: further results', *American Journal of Agricultural Economics,* vol. 71, no. 2, pp. 338–43.

Mullen, J.D., Alston, J.M. and Wohlgenant, M.K. 1989, 'The impact of farm and processing research on the Australian wool industry', *Australian Journal of Agricultural Economics,* vol. 33, no. 1, pp. 32–47.

Mullen, J.D., Wohlgenant, M.K. and Farris, D.E. 1988, 'Input substitution and the distribution of surplus gains from lower U.S. beef processing costs', *American Journal of Agricultural Economics*, vol. 70, no. 2, pp. 245–54.

Muth, R.F. 1964, 'The derived demand for a productive factor and the industry supply curve', *Oxford Economic Papers,* vol. 16, pp. 221–34.

Pannell, D.J. 1997, 'Sensitivity analysis of normative economic models: theoretical framework and practical strategies', *Agricultural Economics,* vol. 16, no. 2, pp. 139–52.

Piggott, R.R. 1992, 'Some old truths revisited', *Australian Journal of Agricultural Economics,* vol. 36, no. 2, pp. 117–40.

Scobie, G.M. and Jacobsen, V. 1992*, Allocation of R&D Funds in the Australian Wool Industry*, Department of Economics, the University of Waikato, Hamilton, New Zealand.

Tulpule, V., Johnston, B. and Foster, M. 1992, *TEXTABARE: A Model for Assessing the Benefits of Wool Textile Research*, ABARE Research Report 92.6, AGPS, Canberra.

Watson, A.S. 1994, 'Economics and the wool industry', paper presented to a conference organised on the occasion of the retirement of Ross Parish, Sydney, 18–19 February.

Wohlgenant, M.K. 1989, 'Demand for farm output in a complete system of demand functions', *American Journal of Agricultural Economics,* vol. 71, no. 2, pp. 241–52.

Zhao, X., Griffiths, W.E., Griffith, G.R. and Mullen, J.D. 1998, 'Probability distributions for economic surplus changes', paper presented to the 42nd AARES Annual Conference, University of New England, Australia, 19–21 January.

Zhao, X., Mullen, J.D. and Griffith, G.R. 1997, 'Functional forms, exogenous shifts and economic surplus changes', *American Journal of Agricultural Economics,* vol. 79, no. 4, pp. 1243–51.