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UNCERTAINTIES OF ESTIMATING THE WELFARE EFFECTS OF AGRICULTURAL BIOTECHNOLOGY IN THE EUROPEAN UNION

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EUWAB-Project (European Union Welfare effects of Agricultural Biotechnology), Project VIB/TA-OP/98-07: "Micro- and Macro-economic Analysis of the Economic Benefits and Costs of Biotechnology Applications in EU Agriculture - Calculation of the Effects on Producers, Consumers and Governments and Development of a Simulation Model"

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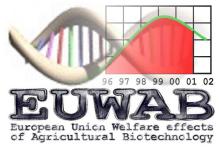
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The EUWAB-project (European Union Welfare Effects of Agricultural Biotechnology)



Since 1995, genetically modified organisms have been introduced commercially into US agriculture. These innovations are developed and commercialised by a handful of vertically coordinated "life science" firms who have fundamentally altered the structure of the seed industry. Enforcement of intellectual property rights for biological innovations has been the major incentive for a concentration tendency in the upstream sector. Due to their monopoly power, these firms are capable of charging a "monopoly rent", extracting a part of the total social welfare. In the US, the first *ex post* welfare

studies reveal that farmers and input suppliers are receiving the largest part of the benefits. However, up to now no parallel *ex ante* study has been published for the European Union. Hence, the EUWAB-project (European Union Welfare effects of Agricultural Biotechnology) aims at calculating the total benefits of selected AgBiotech innovations in the EU and their distribution among member countries, producers, processors, consumers, input suppliers and government. This project (VIB/TA-OP/98-07) is financed by the VIB - Flanders Interuniversitary Institute for Biotechnology, in the framework of its Technology Assessment Programme. VIB is an autonomous biotech research institute, founded in 1995 by the

Government of Flanders. It combines 9 university departments and 5 associated laboratories. More than 750 researchers and technicians are active within various areas of biotech research. VIB has three major objectives: to perform high quality research, to validate research results and technology and to stimulate a well-structured social dialogue on biotechnology. Address: VIB vzw, Rijvisschestraat 120, B-9052 Gent, Belgium, tel: +32 9 244 66 11, fax: +32 9 244 66 10, www.vib.be



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Abstract

In the literature, impact estimates of agricultural biotechnology vary strongly according to the region, the crop, the year, the scale, and the methodology of the study. Therefore, this paper provides a methodological background for analysing, interpreting, and comparing these estimates. All possible uncertainties entailed in the estimation procedure are reviewed as well as a methodology to incorporate them into a stochastic simulation model. This procedure can be used to assess the welfare effects of agricultural biotechnology in the European Union.

Introduction

Benefits generated by adoption of whichever new technology in agriculture cannot be directly observed in reality and have to be estimated by isolating all effects solely caused by the innovation itself, from observable changes in farm-level budget data. However, the underlying theoretical assumptions and empirical data of what finally consists in a 'theoretical abstraction' are subject to a wide range of uncertainties.

The most important uncertainties are associated with the *ex-ante* nature of our research question. Since the technology of which we try to estimate the impact, is not yet adopted on a sufficient scale by the farm sector, empirical farm-level impact data simply do not exist. But even if these data existed, the related *ex-post* impact estimates would still be subject to a large set of uncertainties, measurement problems, biases and errors.

When we try to aggregate these farm-level or 'micro-economic' impact estimates up to an aggregate or 'macro-economic' level, a second set of uncertainties emerges. Some are due to econometric measurement errors while others are related to the partial equilibrium nature of our modelling framework. Moreover, the *ex-ante* setting implies that no information is available yet about the farm sector's innovated input demand (adoption pattern) and input industry's pricing strategies (price premium and technology fee).

Conventionally, research benefits were estimated assuming that the research is publicly funded and innovated inputs competitively sold in the input market. Figure 1 represents the output (a) and input (b) markets surrounding the farm sector. Let $S_0(p)$

be the upward sloping supply curve and D(p) the downward sloping demand curve in the output market for the conventional agricultural commodity being modeled (Figure 1a). The innovation is assumed to be cost reducing, resulting in a shift of the supply curve from $S_0(p)$ to $S_c(p)$ on the condition that the innovated input is competitively supplied. This supply shift leads to an increase in economic welfare, equal to the area ABDE, the so-called *gross annual research benefits* (GARB). The model presented in Figure 1a, has been used for numerous agricultural research evaluation and research priority studies (Alston, Norton, and Pardey, 1995).

However, most of the recent agricultural biotechnology innovations have been developed by private firms protected by intellectual property rights (IPR's), such as patents, which confer monopoly rights to the discoverer (with some limitations). This is a new phenomenon in the agribusiness sector. The result is that prices for these inputs are higher than they would be in a perfectly competitive market. Therefore, Moschini and Lapan (1997) bring along some new elements in the conventional analytical framework. They complete it by including the possibility that the innovation is protected by IPR's in the input market. Thus, the correct evaluation of the benefits from R&D aimed at agriculture needs to account for the relevant institutional and industry structures responsible for the actual development of technological innovations.

The technology is assumed to be cost reducing and this can be visualized in the input market (Figure 1b) by representing input prices in efficiency units, resulting from a one-factor-augmentation model (Moschini and Lapan, 1997). This allows the new, more productive, factor to be measured in the same physical units as the pre-

innovation input. Farmers will adopt the new variety if the price in efficiency units of the new input is less than that of the old input: $w_I/\alpha \le c$. In other words, farmers will adopt a biotechnology variety when the value of the cost reduction plus the increase in yield is greater than the price differential between these varieties. It is reasonable to assume that both types of seeds are produced at a constant marginal cost c. We also assume that the conventional technology is produced in a perfectly competitive input market, so that its price approximates its marginal cost c. However, in the case of the new technology, the IPR's allow the firm to hold a temporary monopoly position, bounded of course by some limit pointed out by Lapan and Moschini (2000).

Let X(w) be the downward sloping demand curve of the farm sector for genetically engineered seed in the input market (Figure 1b). The higher the price w, the lower demand x will be for the improved variety due to the existence of alternative conventional technologies such as chemicals. If the firm is the only player in the market, it faces the demand curve X(w). The marginal return curve MR, or return of an additional unit seed sold on the market, can be easily derived from this demand curve (Figure 1b). The firm will maximize profits by producing an amount GM seed equal to αx_1 , where marginal cost c/α in efficiency units is equal to marginal return MR. Since it is the only player in the market facing demand curve X(w), the firm is able to raise its price above the marginal cost c/α . Even at a price w_1/α , the farm sector is willing to buy αx_1 units of the GM seed variety. This monopoly price w_1/α will maximize firm profits and will allow the firm to regain the high R&D costs via a so-called monopoly rent, represented by rectangle $w_1/\alpha Hlc/\alpha$. Because of the fact that the monopolistic seed price w_1/α is higher than the marginal cost c/α , i.e. the seed price that would emerge in a perfectly competitive market, farm-level benefits are

lower and the corresponding supply shift is smaller. The effects of a departure from the assumption of perfect competition towards monopoly are visualized in Figure 1 by a shift of the supply curve from $S_c(p)$ to $S_m(p)$. Hence, the Marshallian surplus increase equals area ABCF instead of simply area ABDE as in the conventional framework of Alston, Norton and Pardey (1995). However, according to Moschini and Lapan (1997), welfare effects of IPR-protected innovated inputs have to be estimated in the input market, with area $cGHw_I/\alpha$ representing the change in Marshallian surplus. Thus, the correct estimation of total welfare increase is equal to the sum of the shaded areas $cGHw_I/\alpha$ and $w_I/\alpha HIc/\alpha$.

However, equivalent with what Alston, Sexton and Zhang (1997) pointed out in their study, extreme assumptions of monopoly or monopsony seem at least as inappropriate as one of perfect competition. Indeed, different patents exist for the same phenotypic trait, e.g. RR® (Monsanto) and LL® (Aventis) for herbicide resistance. Thus, the ML-model, which focuses on the extreme setting of pure monopoly, might need to be adapted to account for a departure from monopoly to different oligopolistic settings. This can be visually done in Figure 1b by rotating the marginal return (MR) curve towards the demand curve X(w) in the input market (Fulton and Keyowski, 2000). If the MR curve in Figure 1b corresponds to the extreme position of monopoly in the input market, in the case of pure competition this curve would coincide with the X(w) curve. An oligopolistic input market would then be an intermediary situation between these two extremes, with a marginal return curve situated somewhere between MR and X(w). In Figure 1a, a departure from a monopolistic towards an oligopolistic input market can be visualized by shifting the supply curve from $S_m(p)$ to somewhere between $S_m(p)$ and $S_c(p)$.

Micro-economic Level

Agricultural Biotechnology Impact Data from Trials and Surveys

Agricultural biotechnology (agbiotech) impact data can come from five sources, ranked by increasing representativity for estimating the technology-induced farm-level supply shift:

- 1. Laboratory trials;
- 2. Field trials;
- 3. On-farm partial adoption trials;
- 4. On-farm field-level surveys;
- 5. Whole-farm surveys.
- (1) Laboratory trials are insufficient for measuring farm-level impact effects, since they are completely isolated from the biophysical and climatic reality in which farms operate. Since a lot of factors are artificially controlled, these trials only give an idea about the pure yield effects of the variety examined.
- (2) Since 1986, *field trials*¹ with genetically modified organisms take place in different countries. Unlike laboratory trials, field trials are subject to the stochastic forces of nature, so they are a more realistic reflection of the relative performance of different varieties in natural conditions. However, these trials are still completely isolated from the context of a farm. The traditional objective of field trials has been to determine whether there is a statistically significant difference among experimental treatments. These treatments are very often different varieties (in variety trials) and, less often, different pest control regimes or different cultural practices (fertilizer rates, tillage, irrigation, etc.). Two types of field trials can be distinguished:

- 1. Yield trials, measuring yield differences between varieties;
- 2. Yield and pest control trials, measuring yields and differences in input use.

Four sources of bias have to be taken into account when aggregating field trial results up to the farm-level (Marra, 2001). First, yield differences measured by yield trials (holding everything else constant) often measure only the genetic potential to affect yield, while yields measured in pest control trials may capture additional cultural practices that can enhance that genetic potential (Gianessi and Carpenter, 2000). Therefore, where a transgenic crop is pesticide-tolerant instead of pesticide-inherent², simple variety trials may produce yield differences that are less than one would expect to find on farms, tending to under-estimate farm-level impacts. Secondly, the choice of varieties to be compared can also cause a bias in the measured yield difference. In the case of a currently used conventional variety, which is compared to a transgenic variety, the latter is often penalised by the fact that it is not necessarily as well adapted to the biophysical and climatic conditions of the area as is the case with the conventional variety. Varieties are agro-climatically specific, and thus varieties initially released by seed companies may not have been appropriate for all regions, especially the lower adopting regions (Falck-Zepeda, Traxler, and Nelson, 2000b). This will undoubtedly change as traits are genetically inserted in a larger set of varieties. A more accurate method is to compare yields in properly conducted sideby-side trials carried out with near-isogenic lines³ that differ only in the possession of the inserted gene. Such trials are the most reliable way to isolate the consequences of genetic differences, all other things being equal (Benbrook, 1999). Again, the nearisogenic conventional parent of the transgenic variety has generally not been among the set of conventional varieties farmers have chosen to grow in the area. So, although these trials give a direct measure of the genetic yield potential (the change in

yield owing to the transgene only), they may result in an over-estimation of the farmlevel impact of adopting the transgenic variety. In the long run, as more varieties are being genetically transformed, the 'isogenic' comparison will become a realistic assumption for ex-ante evaluations of the benefits of transgenic varieties. Thirdly, side-by-side trials of pesticide-inherent transgenic and conventional varieties (e.g. Bt crops) can be biased by the so-called 'halo' effect. The insect suppression of the Bt crop may spill over onto the conventional treatment, providing another source of pest control, which may increase the yield relative to what it would be if the conventional The measured yield difference between the crop were grown in isolation. conventional and transgenic variety may be biased downward as a result. Finally, biases can also be introduced in the second group of field trials: pest control trials. This is due to the fact that most agricultural scientists manage pests in field trials with the objective of maximizing yield while in real farm situations profit is maximized, not yield. The direction of this bias is difficult to predict if the transgenic crops tested are pesticide-tolerant. In the case of pesticide-inherent crops, the measured pesticide use difference and, thus, the economic impact may be under-estimated.

(3) On-farm partial adoption trials deal with this issue by ensuring that under each technology the set of practices and input mixes that would minimize costs (or maximize profits) is employed. Only the current conventional crop-pesticide system is the relevant counterfactual to compare to the new technology (Alston, Norton, and Pardey, 1995). However, in such experiments biases still can be introduced if some of the decisions are left to the researchers.

- (4) Surveys, and more specifically *on-farm field-level surveys*, such as the area-frame surveys from the USDA's Agricultural Resource Management Study (ARMS) used by Fernandez-Cornejo et al. (2000) and McBride and Books (2000), are a way to However, since there have been avoid potential researcher-induced biases. demonstrated differences between adopters and non-adopters of almost all new agricultural technologies or techniques that can also influence yield, production practices, production costs or returns (Feder, Just, and Zilberman, 1985), the economic impact solely due to the technology cannot be known with certainty from this type of survey. When individual fields are surveyed, isolated from the context of farms, the difference in performance between the transgenic crop and the conventional crop cannot be calculated on each farm under the same management and general growing conditions. It can only be calculated as an average of all selected fields planted with transgenic crop against the average of all fields not planted with the transgenic crop. Marra (2001) did an interesting test to assess the bias introduced by this type of surveys. Using whole-farm survey data from 1996, she calculated economic impacts of Bt cotton in three ways: (1) within an adopting farm, (2) between adopters and non-adopters and (3) as if the data came from a field-level survev. While no particular direction of bias could be assigned to the third methodology, large disparities existed between the three methods regarding differences in yields, insecticide costs and spray numbers.
- (5) Finally, whole-farm surveys asking farmers about the transgenic and non-transgenic acres on their farm, are the only way to hold constant the other factors that can influence the difference between the two. Farmers are optimisers, both in their choice to adopt or not to adopt and in the input choices and production method for

each technology. The Enhanced Market Data⁴ (EMD) used by Falck-Zepeda, Traxler, and Nelson (2000b), for example, compares paired Bt and non-Bt cotton fields with the same agronomic practices and rotations. Although often not available in the public domain, these data provide the most reliable estimates of the farm-level impact of agricultural biotechnology. Table 1 summarizes the findings of this section.

It is clear that impact data issued from methodologies 4 and 5 can only exist when the new technology is already adopted on a sufficiently large scale, i.e. in an *ex-post* research evaluation setting. In our methodology of estimating the aggregate impact of agbiotech in the EU, the *ex-ante* setting due to the absence of widespread farm-level adoption, limits our data pool to the group of field trials (and eventually on-farm partial adoption trials). However, the farm-level and nation-wide experiences since 1996 with genetically modified crops in the USA, Canada, Australia and China provide us extra information about the potential biases introduced by aggregating these field-level data up to the farm-level, country-level and finally the level of the EU (cfr. infra).

This section allows us to draw some important conclusions about interpreting literature on the impact of agbiotech. The test of Marra (2001) illustrates very well how survey methods can change impact estimates. 'Low-grade' estimates (e.g. field-level trials and surveys), although they give some indication about the potential impact, should be interpreted with more care than 'high-grade' estimates (e.g. whole-farm surveys). Given that these low-grade estimates are quoted in the popular press and used by other researchers and interest groups, errors in these estimates can be cause for grave concern. Despite the unprecedented adoption rates of GM crops,

suggesting important farm-level benefits, the popular press continuously questions profitability of these crops using even inconsistent estimates, regardless of the source or survey method. Immediately after the publication of the impact estimates of the USDA's Economic Research Service (ERS), environmental groups have welcomed the 'mixed impacts' as evidence that the claims for GM technologies do not stand up. To illustrate the latter, we report some heads found in the popular press: "Input and yield gains insignificant" (Agra Europe, 1999) as a reaction on the ERS report of Fernandez-Cornejo et al. (2000), "OECD questions GM profitability" (Agra Europe, 2000) as a reaction on the OECD (2000) report, and "GM Rape fails to perform as study reveals erroneous basis for UK field-scale trials" (Natural Law Party Wessex, 2000) as a reaction on the paper of Green and Booth (1999), reporting field trial results of the FACTT-project (Familiarisation and Acceptance of Crops Incorporating Transgenic Technology). The ERS estimates are based on area-frame surveys from the USDA's Agricultural Resource Management Study (ARMS), while the FACTTresults stem from field trials (probably without comparing near-isogenic lines). Both sources are not based on whole-farm surveys, and hence should be interpreted with care and not just regarded as conclusive evidence of the impact of agbiotech.

As Marra (2001) correctly points out, it is important to obtain reliable estimates, firstly in order to create a well constructed objective debate without over- nor misinterpretation of empirical evidence, and secondly because policy makers and consumers will benefit from better estimates of the farm-level benefits since these potential benefits can become the costs of regulation to both consumers and producers in regions such as the EU.

Self-selection Bias

When whole-farm survey data are not available in the public domain, sometimes due to their expensive character, econometric techniques have been used to reduce the self-selection bias in field-level surveys. Farmers' adoption and pesticide use decisions may be simultaneous, due to unmeasured variables correlated with both adoption and pesticide demand, such as the size of pest populations, pest resistance, farm location, and grower perceptions about pest control methods. Self-selection arises because farmers are not assigned randomly to the two groups (adopters and non-adopters), but they make the adoption choices themselves. Therefore, adopters and non-adopters may be systematically different⁵ and these differences may manifest themselves in farm performance and could be confounded with differences due purely to adoption. To eliminate this bias, Fernandez-Cornejo et al. (2000), in an attempt to estimate the impact of adopting genetically engineered crops, develop an econometric model, which corrects for self-selectivity. Furthermore, their model ensures that the pesticide demand functions are consistent with farmer's optimisation behaviour, since the demand for inputs is a derived demand. An expansion of their research can be found in Heimlich et al. (2000).

The bias introduced by self-selection is difficult to predict and depends on geographic, as well as socio-economic variables. In the example of Marra (2001), yield gaps between transgenic and non-transgenic crops differ when not controlled for self-selection. Two opposite contributing factors can be assigned. Farmers who do not adopt GMO's are either (1) less educated with smaller farms and generally lower yields (which would widen the yield gap) or (2) farms with higher yields and less initial pest pressure (which would narrow the yield gap). Lin, Price, and Fernandez-

Cornejo (2001) did an interesting study by comparing impact estimates in 1997 of Bt cotton, herbicide tolerant (HT) cotton and HT soybeans in the US according to three different data sources: (1) mean values for adopters and non-adopters obtained from the ARMS survey (methodology 4), (2) elasticities derived from the adoption-impact model of Fernandez-Cornejo, Klotz-Ingram, and Jans (2000) (methodology 4, corrected for self-selection bias), and (3) the EMD database (methodology 5). The latter is applicable only to Bt cotton produced in the Southern Seaboard and Mississipi Portal regions. Therefore, in Table 2 we represent the impact estimates for the case of Bt cotton adoption in the Southern Seaboard in 1997.

Yields for adopters are estimated to be higher than those for non-adopters in all three data sources (Table 2). However, the yield increase varies across the data sources, ranging from an increase of about 11-12 % based on means of the ARMS survey and EMD database to 21 % based on the elasticity reported by Fernandez-Cornejo, Klotz-Ingram, and Jans (2000). In general, pest control costs for Bt cotton adopters were lower in 1997 than those incurred by non-adopters. However, the differences in pest control costs are quite large, depending on the data source used for the estimation. For example, while pest control costs for Bt cotton adopters averaged about 5-7 % lower than nonadopters in the Southern Seaboard, based on mean differentials between adopters and non-adopters from the ARMS survey and the elasticity-based estimate, the savings reached as high as 60 % based on the EMD data. The estimate of pest control cost savings from the EMD data were obtained from a survey of consultants based on matched pairs of Bt and non-Bt cotton fields, closely resembling a controlled environment, which isolates the effects of factors other than biotechnology itself. The elasticity-based estimate on the other hand, statistically

isolates the effect of biotechnology from other factors. Yet the estimates differ greatly, suggesting a lack of consensus based on empirical evidence available to date. Thus, estimating benefits from biotechnology adoption based on the EMD data (which include comparable cost items as in the ARMS data), such as the study on 1996 and 1997 Bt cotton by Falck-Zepeda, Traxler, and Nelson (2000a), would result in much larger benefits to US farmers than based on other data sources.

Non-pecuniary Benefits

Fulton and Keyowski (2000) provide some empirical evidence that the adoption of herbicide tolerant canola⁶ by Canadian farmers is best understood if the assumption that farmers are identical is relaxed and replaced with the assumption of producers' heterogeneity. Contradictorily, in spite of the fact that average production costs of the GM canola varieties were higher (due to lower⁷ yields) than their conventional counterparts, adoption of these varieties has been very fast (from 4 % of the total canola acreage in 1996 to 69 % in 1999). However, this rapid adoption rate of GM canola in Canada still cannot be explained even if one takes into account producer heterogeneity. This is essentially due to the fact that some benefits escape the traditional measurement techniques used to estimate the economic impact of agbiotech, so that the real benefits perceived by farmers may be higher than the estimates found in literature. Hartley Furtan, an agricultural economist at the University of Saskatchewan, notes that it is difficult to ascertain whether biotechnology has increased the profitability of farmers, because it is hard to attach a monetary value to convenience, which he sites as a major contribute of GM crops (AgraFood Biotech, 2001):

It's an important piece of what is pushing adoption by farmers. Herbicide tolerant oilseed rape provides more flexibility when timing weed control and fewer pesticide applications are required, reducing labour and management costs. But, how to calculate the economic benefit of this flexibility is difficult.

While a lot of farm-level impact studies mention the importance of these non-pecuniary benefits, up to date no study has actually made an attempt to quantify these effects. In a recent paper, Marra (2001) stresses the need for an initial attempt to fill this gap in literature.

Estimating Non-pecuniary Benefits: A Micro-economic Approach

To initiate these attempts and illustrate the non-pecuniary effects of biotechnology on the farm-level we develop a stage-specific production function, inspired by Allen and Lueck (1998). Arable farming is characterized by several distinct stages of production: planting, cultivation, fertilization, pest control, harvesting, and processing. The output q_{s-1} from a specific stage s-1 is an input in the next stage s. For stage s, we define t as the length of the stage or the period during which a stage-specific task has to be carried out in order to maintain the input t at a minimal economical level t and t which depends on the entire production function and exogenous factors like output and factor prices. If the task is not carried out timely, i.e. within the period t, the output of the previous stage is damaged. As a result, fewer inputs are available for the next stages and overall output will be reduced. As an example, we refer to the application of pesticides, which has to occur in a well-defined narrow time period. If timing is not respected, pests and weeds can harm the crop, resulting in severe losses.

At each stage the output depends on farmer effort (e), a capital input (k), and random stage-specific natural shock (θ) determined by such natural forces as pests and weather. Hence, the farmer in our model takes the output from a previous stage as an input into the next stage and makes an optimal effort choice that depends, in part, on what nature did in the prior stage. In particular, for stage s, the stage-specific random input of nature θ_s is distributed with mean 0 and variance σ^2 . Further, agricultural timing problems can be examined by letting $q_s = q(d)$, where q_s is the output for stage s and s is the date at which the stage's tasks are completed. Consequently, the production function for a single stage is $q_s = f_s(e_s, k_s, q_{s-1}(d)) + \theta_s$. In Figure 2 we represent the time dependency of the stage-specific input q_{s-1} via a symmetric function with a unique optimum q^* at the optimum date d^* . Figure 2a is the case of a regular crop, while Figure 2b reflects its GM variety. The timing function of the GM crop is flatter, resulting in a wider timing window, i.e. $L_g > L_T$.

Several conclusions can be drawn from this figure. Firstly, in order to maintain a minimal economical input level of q_{min} , cropping systems based on GM crops can spread their labour and capital over a larger period, *reducing the time specificity of labour and capital*. Hence, labour (e_s) and capital (k_s) costs are reduced because these factors can be used more efficiently, e.g. by renting or contracting. In addition, insect resistant (e.g. Bt crops) and herbicide tolerant (e.g. RR® or LL® crops) crops require fewer pesticide applications, reducing labour and capital costs directly.

Secondly, the optimal date d^* is subject to the random forces of nature. The prediction of d^* requires information and management skills (human capital). The latter are costly and hence, in a lot of cases the date at which the task is carried out, d^l ,

is not the optimal date d^* , but shows a small deviance from it. For a given 'wrong date' d^I , in the case of the regular crop this deviance is more severe in terms of crop loss, than in the case of the GM variety, i.e. $\Delta q_r > \Delta q_g$. As a result, agbiotech decreases financial risk, caused by bad spraying timing, since deviances from the optimal date have a lower payoff. Moreover, less information and management skills are needed in order to estimate d^* , implying lower information and management costs.

Thirdly in some cases, e.g. the case of Bt crops, the variance of the optimal date decreases due to the fact that Bt crops are protected against the European Corn Borer (ECB; *Ostrinia nubilalis* Hübner) throughout the whole season, eliminating entirely the need for ECB insecticide applications at an optimal date. If the variance of d^* declines, the probability that a given date d^I is 'wrong', i.e. not the optimal date d^* , decreases and hence the probability that crop losses occur, i.e. the financial risk due to bad spraying timing, is lower for Bt crops than for their conventional counterparts. Financial risk decreases can be easily translated into monetary terms of farm-level benefits. It is important to note that this increased flexibility can occur in two subsequent stages. Bt crops for example are continuously protected against the ECB and hence timing is less a problem in the planting as well as the crop protection stage.

However, even if Bt crops lower financial risk associated with bad spraying timing, in a recent article⁸, Hurley, Mitchell, and Rice (2001) remarkably disprove the common perception that Bt corn reduces overall profit variability and, hence, risk⁹. After developing a conceptual model decomposing the value of Bt corn and determining the impact of Bt corn on profit variability, their empirical model finds that Bt corn increases profit variability and thus decreases the value of Bt corn by 10-25 %

depending on risk preferences. This is due to the fact that, when a technology fee is charged, Bt corn increases the potential downside risk and decreases the potential upside risk. The magnitude of these adjustments for risk aversion imply that ignoring the variance increasing impact of Bt corn leads to a significant bias in estimating the value of Bt corn.

Estimating Non-pecuniary Benefits: A Bio-economic Approach

In this section we explore a path for research for the calculation of non-pecuniary benefits of insect resistant crops (e.g. Bt corn) via bio-economic models inspired by entomology. Since 1985, two researchers of the INRA (Institut National de Recherche Agronomique) in France have done excellent research on the modelling of the European Corn Borer (ECB), one of the major maize pests in France (Got, 1988, Labatte and Got, 1993, Got et al., 1994, Got, Labatte, and Piry, 1996, Labatte et al., 1996, Got et al., 1997, Labatte et al., 1997).

Conventionally, control efficacy was analysed by examining the relationship between control and infestation on the one hand and control efficacy on the other hand, considering the mechanism at work between the two variables as a 'black box'. Trials were often conducted in laboratory, yielding biased estimates because they were isolated from the biophysical and climatic context of the field. Labatte et al. (1996) propose a methodology to 'open the black box' and examine the biologic relations which interrelate the different components of pest control (Figure 3b). The result is a bio-economic model, composed of several sub-models, which can be used to predict optimal pesticide application dates and rates and to understand the underlying mechanisms of pest populations and control. Environmental factors (crop, climatic

factors) are linked to biological cycles of the damaging insect (larval development, distribution and mortality) and finally to economic variables such as control efficacy or pest control productivity. Since the stochastic nature of some environmental factors (e.g. temperature) are well documented, these models can give us ideas about the random forces of nature experienced by farmers and their implications on risks, task timing and flexibility and management. Quantifying these forces via statistical distributions and bio-economic relations can provide an excellent and original methodology for estimating the non-pecuniary benefits of Bt corn by comparing the latter technology with conventional pest control techniques.

In conclusion, the overall effect of agricultural biotechnology is that this technology decreases the dependence of the cropping system on the stochastic forces of nature, allowing for a more flexible task schedule, lower risks and less information and management costs. These non-pecuniary benefits can be translated into pecuniary terms and added to the pecuniary benefits to estimate the total farm-level impact of agricultural biotechnology. These impact estimates will be a better reflection for the rapid adoption rates observed in the USA and Canada since 1996. Similar as in previous sections, conclusions can also be drawn about the interpretation of impact estimates reported in literature. Since most of the estimates are based on directly observable variables such as yields, seed prices and pesticide costs, they only provide a part of the picture. These data probably underestimate the perceived benefits and costs of a farmer who optimises a production system and operates in a real biophysic, climatic and economic environment. Again these incomplete figures are quoted in popular press and used by other researchers and interest groups to influence policy makers, distributors and consumers. Hence, the only complete estimate of the impact

of agbiotech is one, which is based on (1) whole-farm surveys and completed with (2) non-pecuniary elements. However, in reality the necessary data are costly or difficult to obtain or simply non-existent, such as in *ex-ante* studies. In the latter case, assumptions have to be made, combined with extensive sensitivity and scenario analyses to take into account all possible outcomes.

Uncontrolled Stochastic Factors

Due to the stochastic nature of pest attacks and weed proliferation (cfr. supra), pest control costs vary substantially in time (from one year to another) and in space (between regions, farmers, and even fields). As a result, farm surveys typically reveal a wide statistical distribution of pest control costs. Some agbiotech innovations, e.g. herbicide tolerant crops, not only decrease average pest control costs, but also their variance since the innovated techniques are more standardised and require less accurate task timing (cfr. supra), less on the spot decision making, less pest information and less management skills. Hence, the benefits of agbiotech are also stochastic since they are calculated by comparing two stochastic variables: conventional and agbiotech pest control costs. According to the year, the region, the farmer, and the field, agbiotech innovations will pay or not. Typically in low infestation years or regions, these innovations yield negative returns due to their relatively high price premium. However, in a lot of cases these negative returns are overcompensated by the perceived risk-decreasing benefits of agbiotech in ex ante. so that they can be regarded as a risk premium paid by the farmer in order to protect his crops against pest attacks. As a result, even if a region may have 'lost' in an ex post analysis, in an ex ante analysis this would have been a winning strategy (Falck-Zepeda, Traxler, and Nelson, 1999).

Extrapolation issues

Until now, the few published studies calculating the welfare effects of agricultural biotechnology are applied on typical US export crops like cotton (Falck-Zepeda, Traxler, and Nelson, 2000b) and soybeans (Moschini, Lapan, and Sobolevsky, 2000). The major difference with the EU is the fact that these American studies regard an *expost* setting, while the recent moratoriums on GMO's in the EU and the absence of empirical farm level adoption impact data oblige us to use *ex-ante* assumptions about yield increases, cost reductions and technology fees. A major question is to what extent the US adoption data can be extrapolated to the EU. Since several conditions (biophysical environment, climate, pest pressure, input use and demand and other market conditions) strongly differ between both regions, extrapolation is hardly possible. However, the empirical farm-level adoption data in the US provide us extra information about how the available EU data, primarily coming from field trials, can be realistically aggregated up to the farm-level, country-level and finally the level of the EU (cfr. supra).

Disaggregation Problems in Aggregated Farm Budget Data

The most crucial parameter for estimating the farm-level impact of agbiotech is the supply shift or *K-factor*, which is a combination of the yield-increasing and cost-reducing effect of the technology and its technology fee. The estimation of the K-factor requires detailed farm cropping budget data for a representative sample of farms in all member countries of the EU. However, disaggregated farm budgets displaying herbicide costs, weeding costs (labour and equipment) and insecticide costs (scouting, application, equipment) are difficult to obtain for all countries. To illustrate the level of detail required to assess the farm-level impact of biotechnology,

Table 3 represents a farm budget of an "average" sugarbeet grower in the UK. The data have been collected via the survey "Crop Profitability Initiative" (CPI) on a sample of 300 sugarbeet growers, organized by British Sugar (Limb, 2000). In the case of genetically modified herbicide tolerant sugarbeets, the most crucial point to estimate is the total cost spent on the weeding operation (herbicides, tractor hoeing and chemical application costs). In the case of Bt corn, this would be the cost of European Corn Borer (ECB) damage despite the use of pesticides, plus insecticide costs plus scouting and application costs. However, since the percentage change in total costs has to be calculated, total farm cropping budgets are needed.

The Farm Accountancy Data Network (FADN) is an instrument for evaluating the income of agricultural holdings and the impacts of the Common Agricultural Policy. The concept of the FADN was launched in 1965, when Council Regulation 79/65 established the legal basis for the organisation of the network. It consists of an annual survey carried out by the Member States of the European Union. The services responsible in the Union for the operation of the FADN collect every year accountancy data from a sample of the agricultural holdings in the European Union. Derived from national surveys, the FADN is the only source of micro-economic data that is harmonised, i.e. the bookkeeping principles are the same in all countries. Holdings are selected to take part in the survey on the basis of sampling plans established at the level of each region in the Union. The survey does not cover all the agricultural holdings in the Union but only those, which due to their size could be considered commercial. The methodology applied aims to provide representative data along three dimensions: region, economic size and type of farming. While the European Commission is the primary user of analyses based on FADN-data,

aggregated data can be found in the 'Standard Results' database. However, FADN data are highly aggregated, adding up all pesticide costs (herbicides, insecticides, and fungicides) for all crops into a single cost entry per holding: "plant protection products". Despite this aggregation problem, there is still a possibility to break down these farm-level aggregates into crop-specific costs. Desbois (2000) reviews an econometric estimation procedure, based on an input-output matrix, and enabling to break down farm-level production costs into crop-specific cost items. He applies this estimation procedure to the French arable sector. His methodology features three steps:

- econometric estimation of technical production coefficients reporting production costs per crop;
- 2. determination of individual production costs (per holding) by inserting the residuals of the econometric model proportionally to the outputs;
- breaking down labour (family and hired) costs proportionally to the crop margins.

Paris and Howitt (1998) propose an alternative methodology based on a methodology originated in science: maximum entropy (ME). Since 1957, physicists, statisticians, astronomers, engineers, medical doctors, and policemen have used the ME methodology to great advantage. For example, an ME algorithm is used to recover the license plate of a speeding car by enhancing an illegible photograph that is completely out of focus, called an 'ill-posed' image. The list of practical uses of ME is extensive. In all these cases, the objective of the analysis is that of recovering an acceptable and informative image (estimated model) from limited (out-of-focus) information associated with an ill-posed problem.

The originality of Paris and Howitt (1998) and their predecessors consists in the fact that they translate these theories from science to modern econometrics. Production economics are often ill-posed. This means that the number of parameters to be estimated is greater than the number of observations. In our case of aggregated input data, the input information is frequently represented by the total cost of input categories, which often are not broken down on a per activity basis. The authors show that it is possible to exploit all the available information (no matter how scarce) to the maximum extent by adopting a suitable and consistent approach using the maximum entropy formalism. A remarkable feature of the ME approach is the ability to exploit all the available information regardless of sample size. Even for a single set of observations, a variable cost function can be recovered for a firm. This is precisely the uncommon and novel aspect of this approach. Hence, the ME methodology potentially offers a solution to the aggregation problem in the typically highly aggregated farm budget data of the European Union's FADN network.

However, the main reason for the lack of adoption of the ME formalism in econometrics is to be found in the requirement for an a-priori specification of support intervals and probabilities. This subjective information that must be provided by the researcher, affects the parameter estimates in unpredictable ways. Therefore, in a more recent paper, Paris (2001) developed the 'Leuven estimator' in, inspired by the theory of light. Light carries information. Hence, it seems proper that its theory might be taken as a source of inspiration for the analysis of information contained in sample data. The major innovation of his recent paper is the fact that he proposes a new class of ME estimators, e.g. Leuven 1, Leuven 2, etc., that does not depend upon any a-priori information and does not require the specification of support intervals.

These novel estimators overcome the weakness of the ME estimator and allow the analysis of ill-posed (and well-posed) models using a maximum entropy approach without requiring any subjective information. Using Means Squared Error (MSE) loss function as a criterion, the class of Leuven estimators seems to perform competitively against all known estimators both in the case of ill-posed and well-posed models.

Aggregate Level

Model Specification Uncertainties

A first model specification uncertainty can be found in the discussions on the nature of the research induced supply shift: pivotal (convergent or divergent) or parallel. The point was first addressed by Lindner and Jarrett (1978), leading to some debate, with comments from Rose (1980) and Wise and Fell (1980) and a reply by Lindner and Jarrett (1980). Lindner and Jarrett (1978) show that the estimation of research benefits is extremely sensitive to assumptions about the nature of the supply shift. For example, given a linear supply function, total benefits from a parallel shift are almost twice the size of total benefits from a pivotal shift. When supply shifts in parallel, producers always benefit from research unless supply is perfectly elastic or demand is perfectly inelastic, and even in these extreme cases, producers are no worse off as a result of research. On the other hand, with a pivotal shift, producers benefit only when demand is elastic. When demand is inelastic, producers necessarily lose from a pivotal shift. While the authors provide some intuition¹² to predict whether a particular innovation will produce divergent, parallel, or convergent supply shifts, Rose (1980) contends that this prediction is virtually impossible ¹³. Given this statement and in the absence of information required to choose a particular type of shift, Alston, Norton, and Pardey (1995) recommend employing a parallel shift, persuaded by Rose's (1980, p. 837) suggestion:

For most innovations, the best information available may be a cost-reduction estimate for a single point on the supply curve. ... [It] is unlikely that any knowledge of the shape of the supply curve, or the position at which the single estimate applies, will be available. The only realistic strategy is to assume that the supply shift is parallel.

We agree with Beattie (1995) that a more definite answer is needed to fill this gap in the literature. What is important is to have an understanding of supply curves and the derivation of cost changes (Rose, 1980). In the literature on the aggregate impact of agbiotech, both types of supply shift appear. Falk-Zepeda, Traxler, and Nelson (2000a, 2000b) and Price, Lin, and Falck-Zepeda (2001) use a parallel shift while Moschini, Lapan, and Sobolevski (2000) opt for a divergent pivotal shift of the supply function (cfr. infra).

A second model specification uncertainty is centred on the discussions about the functional form of the supply and demand functions. Two frameworks have frequently been used in empirical work on evaluation of research benefits:

- Linear demand and supply functions, respectively $P = a \alpha Q$ and $P = b + \beta Q$, with $\alpha = P/\eta Q$ and $\beta = P/eQ$, where η and e denote the own price elasticity of demand and supply at the initial equilibrium;
- Nonlinear constant elasticity (NLCE) demand and supply functions, respectively $P = AQ^{-\sigma}$ and $P = BQ^{\gamma}$, with $\sigma = 1/\eta$ and $\gamma = 1/e$.

Voon and Edwards (1991) compare both models and conclude that the calculated benefits of research using the linear model are substantially larger than those using the NLCE model when the price elasticity of supply for the commodity is significantly lower than unity. However, when the elasticity of commodity supply is greater than one, the calculated research benefits are considerably smaller than those calculated using the NLCE model. The authors argue that commodity supply curves in agriculture are more likely to take the constant elasticity form. Moreover, with inelastic supply at the initial equilibrium, a linear supply curve passes through the negative fourth quadrant. An extrapolation of the linear inelastic commodity supply curve to this quadrant (i.e. production of the commodity at negative prices) is unrealistic. This problem is avoided by the use of constant elasticity supply curves, since these curves pass through the origin. The authors conclude that the use of an NLCE specification and a pivotal shift due to research is preferable to use of a linear supply curve with pivotal shift. The issue whether measuring cost reductions and research benefits in the negative quadrant is correct, has been debated by Elbasha (1997), but convincingly defended by Edwards and Voon (1997).

Zhao, Mullen, and Griffith (1997) finally shed additional light on the issue. They show that when demand and supply curves are locally linear and there is a parallel shift in demand and supply, the economic surplus changes are exact if percentage change of prices and quantity is defined¹⁴ as $E(.) = \Delta(.)/(.)$. When demand and supply curves are locally log-linear (NLCE) and there is a proportional (pivotal) shift, the price, quantity, and surplus changes are exact if percentage change is defined as $E(.) = \Delta ln(.)/(.)$. In empirical applications, the errors in estimates of both price and quantity changes and economic surplus changes are small as long as the shift is small,

whatever the form of the true demand and supply curves. The authors conclude that additional data, such as the distribution of firms by cost structure and how technical change affects these different firms (i.e. producer heterogeneity, discussed by Demont and Tollens (2001a)), are needed to accurately calculate producer surplus changes.

In the literature on the aggregate impact of agbiotech, both types of supply functions coexist. The linear model is used by Falk-Zepeda, Traxler, and Nelson (2000a, 2000b) and Price, Lin, and Falck-Zepeda (2001). Moschini, Lapan and Sobolevski (2000) on the other hand, develop a NLCE model, adapted to the actual working of the herbicide tolerance innovation and apply it to the case of RR® soybeans. They develop an aggregate NLCE supply function incorporating four technology-specific parameters enabling to parameterize the herbicide tolerance innovation in detail:

$$q = \lambda \left[\underbrace{A + \rho \alpha + \frac{(1 + \rho \beta)G}{1 + \eta} p^{1 + \eta} - \delta w (1 + \rho \mu)}_{\text{average profit per hectare } \overline{\pi}} \right]^{\theta} (1 + \rho \beta) A p^{\eta}$$
 (1)

aggregate supply of land to soybean production $L = \lambda \overline{\pi}^{\theta}$

General Parameters:

 λ = scale parameter;

A, G = parameters subsuming all other input prices, presumed constant;

 η = elasticity of yield with respect to sugarbeet price;

 δ = constant optimal density of seeds;

w = price of seed:

 θ = elasticity of land supply with respect to sugarbeet profit per hectare.

Technology-Specific Parameters:

 α = coefficient of unit profit increase due to the HT technology;

 β = coefficient of yield change due to the HT technology;

 $\rho \in [0,1]$ = adoption rate;

 μ = markup on HT seed price (reflecting technology fee).

Due to a comment of Moschini (Lin, 2001, personal communication), Price, Lin, and Falck-Zepeda (2001) recalculated their model using a NLCE framework, but found no significant difference in the outcomes of the two models. However, the main advantage of the methodology of Moschini, Lapan and Sobolevski (2000) lies in the elegance with which first wave agbiotech innovations can be modeled. Therefore, the latter methodology is used in our case studies on the welfare effects of agricultural biotechnology in the European Union (Demont and Tollens, 2001b).

A third model specification issue is centred on the validity of consumer and producer surplus measures and on the conditions that must hold if these estimates are to provide an accurate indicator of changes in social welfare. There are several alternative measures that have been proposed as money metrics for the consumer welfare change due to price changes: Marshallian (1890) consumer surplus¹⁵ and producer surplus¹⁶ on the one hand, and Hicksian (1948) equivalent variation¹⁷ and compensating variation¹⁸ on the other hand. The use of Hicksian demand curves leads to more correct welfare measures, while Marshallian measures are biased. Recent empirical evidence on the French food industry warns for the use of Marshallian welfare calculations (Lavergne, Réquillart, and Simioni, 2001). The authors estimate the welfare loss (deadweight loss) due to market power using real data on twenty-one sectors of the French food industry. In each case, the Hicksian welfare loss is significantly different from the Marshallian welfare loss at a 5 % level. For the sugar industry for example, they obtain Hicksian welfare losses that are 21 % to 24 % higher than the Marshallian ones. This leads them to conclude that the Marshallian welfare measure is a poor approximation of the exact Hicksian welfare loss, and that the latter should be used in applied welfare analysis.

However, Alston, Norton, and Pardey (1995) argue that, since the parameters of a welfare analysis are stochastic, correcting for the income effect, by introducing a (stochastic) income elasticity of demand in a Hicksian methodology, adds an additional source of imprecision in the welfare measures. Hence, there may be a trade-off of variance against bias. This weakens the arguments in favour of correcting for income effects to obtain Hicksian welfare measures. Moreover, when the income effect associated with price changes is small, consumer surplus is not a bad approximation. In developing countries price changes of staple foods, e.g. banana or cassava, can generate substantial income effects, but even in that case, the income-effect bias is likely to be swamped by errors in measuring positions of curves or shifts in them.

The same discussions hold for the use of producer surplus in welfare measures. The income effect associated with a change in a factor or product price is often substantial, making producer surplus a much less reliable measure of the corresponding equivalent variation or compensating variation. Producer surplus measures the return to fixed or quasi-fixed factors and thus may be thought of as corresponding closely to the concept of economic profit: income over and above the opportunity costs associated with variable factors. However, *changes* in producer surplus are likely to provide a more accurate reflection of changes in profit, especially when the effects of relatively small changes in prices are measured.

What are the implications of these discussions for our case study on the welfare effects of agricultural biotechnology in the European Union's sugar sector? Since EU aggregate internal demand for sugar does not interfere in the model (Figure 4) due to

the EU's Common Market Organisation for sugar, no measurements along the EU demand curve have to be carried out and hence no model specification errors are introduced in the estimation of EU domestic welfare effects on consumers. Estimating the welfare implications on consumers in 'the rest of the world' (ROW), as a region, on the other hand, does not escape these methodological difficulties (Demont and Tollens, 2001b). Again, this bias will be largely swamped by imprecision, uncertainties and lack of information regarding data like technology spillovers, potential adoption, production costs, supply and demand elasticities and technology prices in the ROW.

To conclude this section, we agree with Alston, Norton, and Pardey (1995, p. 48) that:

... there are a number of sources of potential errors in the analysis and attention ought to focus on the more important ones, which in this case are not due using consumer surplus instead of either the exact money metric or an approximate measure of compensating or equivalent variation.

Supply Shift

The size of the research-induced supply shift, the K-factor, is a crucial determinant of the total benefits from research. According to Alston, Norton, and Pardey (1995), three possible K-factors can be distinguished, depending on their accuracy and completeness. The first factor (k_1) is the shift that would occur if the new technology were adopted, but the input mix were the same as under the original technology. The second factor (k_2) represents the shift after optimisation of the input mix, but this assumes that variable input prices and the quantities of 'fixed' factors (such as land) used in producing the commodity are fixed. The difference between both shifts is the

cost saving due to optimising the input mix for the new technology. In the case of herbicide tolerant crops for example, less herbicides, time-specific labour (cfr. supra), information, and management are needed. After adoption of the technology, these inputs can be gradually reduced generating extra costs savings, in addition to the yield-increasing effects of the innovated seeds. Finally, k_3 represents the supply shift after all optimising responses have been made, including the drawing of 'fixed' factors into (or out from) the production of the commodity whose profitability has been increased by the introduction of the new technology. Adoption of herbicide tolerant crops for example, increases the profitability of the crops. As a result, in the medium and long run more land will be allocated to these crops.

Which of these supply shifts should we attempt to approximate in order to include them in our assessment of the impact of agbiotech? The research-induced cost saving is understated by k_I because it does not allow for economising the input mix. The unthinking use of experiment data (field trials) could lead unconsciously to a measure that corresponds to k_I unless explicit account is taken of the input-mix change. Adjusting for the optimal input mix would lead to a measure that corresponds to k_2 . This shift could be derived from a thoughtful *ex ante* study based on experiment data. The estimate of the research-induced supply shift from an *ex post* econometric estimation of the adoption of the agbiotech innovation might correspond to k_3 , which represents the entire research-induced supply shift, including the component of cost reduction (or output increases) that is attributable to drawing in quasi-fixed factors (e.g. allocatable factors such as land in a multi-output setting). The problem is that the measure of k_3 here is a measure of *single-commodity* cost changes, some of which have been achieved at the expense of cost increases in other commodities, from the

production of which quasi-factors have been drawn. The difference between k_2 and k_3 is not a net benefit. It is a gross benefit for which there is a corresponding cost associated with a leftward shift (negative K-factor) of the supply of competing products and the net social benefit is zero. Unless a full general-equilibrium analysis (see next section) is being undertaken, in which case it would be desirable to explicitly measure the impact of commodity-market and factor-market interactions, it would be best to attempt to estimate k_2 rather that k_3 (Alston, Norton, and Pardey, 1995)¹⁹.

In the first section of this paper we already emphasised the role of accurate agbiotech impact data and showed how the impact estimates differ according to three different data collection methodologies (Table 2), by referring to the farm-level impact study of Lin, Price and Fernandez-Cornejo (2001). Since these impact estimates are at the base of welfare measures, their accuracy is of great importance to any aggregate macro-economic impact study. To illustrate this, Price, Lin, and Falck-Zepeda (2001) compare the welfare estimates for Bt cotton obtained with the same three data sources: (1) mean values for adopters and non-adopters obtained from the ARMS survey (methodology 4 in the first section), (2) elasticities derived from the adoptionimpact model of Fernandez-Cornejo, Klotz-Ingram, and Jans (2000) (methodology 4 corrected for self-selection bias), and (3) the EMD database (methodology 5). Their results show remarkable differences between the three datasets both in the size of total world benefits (ranging from 140 to an amount twice as much, i.e. 285 million USD) and their distribution among farmers, input suppliers, and consumers. Farmers' share of the benefits ranges from roughly one fifth (with one half captured by the input suppliers) using the ARMS dataset, via one third (equally shared with the input

suppliers), to one half (with one fourth accruing to input suppliers). In other words, the accuracy of the dataset determines whether the major winners are either farmers (EMD dataset), or input suppliers (ARMS dataset).

General Equilibrium Feedbacks

The prices of inputs are exogenous to individual firms, but endogenous at the industry level, giving rise to the possibility of 'general equilibrium feedbacks' from the input markets. Such changes complicate both the problem of measuring the research-induced supply shift and the problem of interpreting it in relation to a welfare analysis and evaluation (Alston, Norton, and Pardey, 1995). This is especially the case for *ex ante* evaluations, where the potential adoption of the innovated inputs (e.g. herbicide tolerant sugarbeets) and disadoption of the old technology (e.g. conventional herbicides) are not known with certainty. Expanded use of the new technology and contraction of the old will, in general, change demands for all factors if these technologies have different input requirements, and hence change the respective input prices. Recognising the endogeneity of input prices, in effect, transforms the standard partial equilibrium model of adoption of innovations into a general equilibrium model in which the producer of the innovated inputs recognises the impact of his actions on other input prices.

Lapan and Moschini (2000) show that the optimal pricing strategy of an innovating monopolist of a technologically superior intermediate input, typical for agbiotech innovations, may lead to incomplete adoption when the price of the alternative (competitively supplied) input is endogenous and altered by adoption of the innovation. The fact that adoption is not complete means that an additional source of

inefficiency arises from the monopoly pricing of the new input: pure production inefficiency because an inferior technology is used when a superior technology is available.

Prior research shows that, with complete information, the monopolist's optimal strategy will lead to complete adoption of this technologically superior innovation. This is partly attributable to the partial equilibrium nature of prior models. Heterogeneity among users, uncertainty and information considerations are among the explanations that have been offered to explain the time path of adoption. But in most models of diffusion the premise is that, eventually, the adoption of a superior technology will be complete. Therefore, the authors address the question of how the innovator's optimal pricing policy is affected when the adoption of the innovation may change the price of some other input used by final producers. Innovations that alter the way goods are produced (process innovations) will change not only production costs, but also the relative demands for inputs, and thus have the potential to change their equilibrium prices. Herbicide tolerant and insect resistant crops for example are having dramatic effects on the composition of farmers' demand for herbicides and insecticides in the US. Furthermore, because yield increase is a significant attribute of these innovations, the change in profitability of these transgenic crops affects demand for land and hence its price.

Previous models concerning pricing and adoption of an innovation have held other input prices constant. In their *ex ante* evaluation of the potential adoption of herbicide tolerant oilseed rape in France, Desquilbet, Lemarié, and Levert (2001) include the possibility that the price of the conventional technology (i.e. conventional herbicides)

is altered. However, they do not attempt to model the adoption and the price reaction of the suppliers of conventional herbicides, but assume a fixed decline of 30 % of the herbicide price.

Assessing general equilibrium feedbacks due to adoption of new technologies and disadoption of old technologies is difficult for *ex ante* evaluations, due to the lack of data and the presence of uncertainties, especially in the case of the current controversies about agricultural biotechnology. For our *ex ante* framework, Moschini (2001) recommends to assume, at a first pass, that the competitively supplied alternative technology is produced at a constant unit cost, i.e. no price decline is possible. This is a simplification, but at least it provides us with a (relatively easy) benchmark. He further suggests keeping the simulation model as simple as possible at the beginning, while including some sensitivity analysis on the parameters that are believed to be critical.

Adoption Pattern, Technology Pricing and System Dynamics

But even when general equilibrium feedbacks are difficult to assess, these phenomenons are only part of a larger, more complex system of technology adoption. The adoption of agricultural technologies has been studied intensively (Feder, Just, and Zilberman, 1985, Abadi and Pannell, 1999) since Griliches' (1957) pioneering work on adoption of hybrid corn in the US. More recently, this literature is being reviewed and applied on the recent adoption of agricultural biotechnology innovations in the US (Hebert and Goldsmith, 2000, Nadolnyak and Sheldon, 2001). Technology firms need to understand the biotechnology adoption process in order to develop marketing and pricing strategies compatible with the new state of the technology

involving stacking, bundling, input systems, new user groups, and intellectual property. Government stakeholders too have an interest in the adoption process as they explore regulatory and welfare issues associated with proliferation of these technologies. This process is endogenous as R&D firms, potential adopters, and government institutions all interact simultaneously creating complex adoption decision rules. Unfortunately, previous work looking at biotechnology adoption has, for the most, been static in nature and overly dependent on exogenous variables (Chung and Buhr, 1997, Alexander and Goodhue, 1999, Moschini, Lapan, and Sobolevsky, 2000).

Therefore, Hebert and Goldsmith (2000) show that the modelling of agbiotech seed adoption requires the integration of multiple factors in a dynamic environment. Previous approaches though have tended to look at technology adoption from a reductionist view, considering only a few issues at a time. While making the problems more tractable, misspecification of complex interactions could occur (Chung and Buhr, 1997). System Dynamics (SD) may be effective in modelling systems reflective of such complexities. SD is a modelling approach based on system thinking. That is, understanding organizational behaviour is best conducted using a systemic perspective that combines both individualistic and holistic approaches, inclusion, rather than reduction and narrowing (Hebert and Goldsmith, 2000). Using four biotech crops (Bt corn, Roundup Ready® Soybeans, RR Canola, and Bt cotton), the authors validate the model employing three validation procedures. Sensitivity analysis is conducted opening the "black-box" of the model and identifying the forces driving adoption. Finally scenario analysis is employed to analyse an example of a policy and marketing issue related to biotechnology input supply.

In Figure 5, we show an adaptation of the mental representation of Hebert and Goldsmith's (2000) model. This representation identifies components and variables that are considered in the model. From this, causal-loops and influence diagrams are constructed. The model distinguishes seven elements: yield increase, yield variance, variable costs, production constraints (e.g. the obligation to plant refuge zones), complexity, uncertainty, and output heterogeneity (the presence of a price premium for non-GM output). Both market and firm level impacts are parts of an endogenous process. At the introduction of the new technology, the potential adopters make a decision based on the perception of the economic profitability they have about the innovation and based on the needs of their production system. As they adopt, they learn by obtaining more information about this new technology and by improving their skills at its management. These learning components provide feedback to the producer's economic perception of the profitability of the crop. Additionally, the adoption process is being affected by exogenous influences such as the state of R&D and market prices that add information along the process. The aggregate adoption levels of the agbiotech innovation and disadoption levels of the conventional technology inform the input suppliers about the demand for the two respective technologies. Prices of both technologies will be modified by the input industry according to the objective of profit maximisation. Changes in prices, on their turn, alter the technology characteristics and the relative profitability and adoption of the new technology. The result is a dynamic system, which potentially never reaches a state of equilibrium when new innovations are being developed and transferred to farmers in a continuous process. As a result, the possibilities to predict a reliable adoption pattern are very limited for ex ante studies.

Moreover, these models are still mainly based on technological and economic variables, such as prices and profit. However, the current consumer backlash against GM food, activists' destruction of GM fields and moratoria on planting GM crops in the EU, illustrate that also political and social factors are part of the adoption process. Therefore, the conventional models of agricultural technology adoption based on profit will perform less accurately in predicting the potential adoption of GM crops in the EU.

More specifically in the case of the European Union's sugar sector, predicting the adoption pattern for GM sugarbeets is strongly hampered by the fact that sugarbeets are entirely produced under contract with sugar processors on the one hand, and the fact that the processing sector (processors and transformers) is very concentrated on the other hand. Hence, the decisions regarding the use of sugar produced from GM sugarbeets of important transformers, like e.g. Coca Cola, will determine the demand for GM sugarbeets of sugar processors, while the latter will finally determine GM sugarbeet adoption, instead of the sugarbeet growers themselves. It is questionable whether any adoption of GM sugarbeets will take place in the short run, given the current uncertainties about demand for GMO's in the EU. However, even in the no-adoption scenario, the objectives of our study can be easily redefined. In that case, instead of predicting the expected impact of adopting GM sugarbeets, the objective turns into assessing the benefits forgone, or costs, of a partial of complete rejection of a technology that is capable to improve production efficiency.

Econometric Measurement Errors

Besides the K-factor, crucial parameters for the estimation of the impact of agbiotech are estimates of the response of agricultural supply to movements in expected price and estimates of the response of consumer demand to observed price changes. Both are structural parameters of the simulation model and can be computed as elasticities, reporting the percent change in supply or demand for a one percent increase in price. If available, these elasticities are often taken from previous studies in literature. When interpreting and using elasticities from literature, it is important to check their accuracy and reliability. Usually, not only the estimates vary, but also the models both in terms of specification and sample data used (Jongeneel, 1997). Therefore, model specification and number of observations give an indication about the accuracy of the estimates. The Nerlove model of agricultural supply response is one of the most successful in applied econometrics, as evidenced by the hundreds of subsequent studies that use it productively. The model can be rewritten in a reduced-form equation relating output in period $t(Q_t)$ as a function of observable variables, i.e. lagged price (P_{t-1}) , lagged output (Q_{t-1}) , some lagged (Z_{t-1}) and non-lagged (Z_t) exogenous variables, and an error term ε_t (Poonyth, 1998):

$$Q_{t} = \alpha + \beta_{1} P_{t-1} + \beta_{2} Q_{t-1} + \beta_{3} Z_{t} + \beta_{4} Z_{t-1} + \varepsilon_{t}$$
 (1)

Supplementary statistics, when reported, can give an idea about the reliability of the estimated model. Estimates of the R^2 reflect the goodness-of-fit of the model. Poonyth et al. (2000) for example, use own acreage response elasticities for the European sugarbeet sector, estimated on the data period 1977/78-1995/1996, i.e. n = 19. In Table 4 we represent the estimates of their area-harvested model. Instead

of output Q_t , area harvested A_t is modelled as a function of area harvested in the previous period A_{t-1} , price P, and three exogenous variables: quota quantity, price of a competing crop (wheat) P_c , and a trend variable. The equations of large producers like Belgium, Denmark, France, Germany, UK, Ireland, and Sweden have a fairly high R^2 , while The Netherlands, Spain, Italy, Austria, and Finland have equations characterised by a lower R^2 . In general, the goodness-of-fit seems to be satisfactory, since between 65 % and 99 % of the variance is explained by the model.

When the regression includes lagged dependent variables, typical for supply response models, the Durbin-Watson D-statistic is not valid as a test for autocorrelated residuals (Neter, Wasserman, and Kutner, 1990). In that case, the Durbin H-test can be considered as a valid alternative. For 'large samples' the test statistic has a standard normal distribution. Therefore, for a test of the null hypothesis of no autocorrelation against the two-sided alternative of autocorrelated errors, at a 5 % level, the decision rule is if -1.96 < H < +1.96 do not reject the null hypothesis. Table 4 shows that this condition is fulfilled in all equations. However, this test may not be accurate in 'small samples', again, typical for supply response models in general and more specifically for the reported estimates, which are based on only 19 observations.

Agricultural supply response estimates display curiously large variation across crops, regions, and time periods. This has been noted by numerous studies using elasticities from literature for their simulation models (Jongeneel, 1997, Davis and Espinoza, 1998, Falck-Zepeda, Traxler, and Nelson, 2000b, Price, Lin, and Falck-Zepeda, 2001). Diebold and Lamb (1997) argue that this anomaly may be traced, at least in part, to the statistical properties of the commonly used econometric estimator, which

has infinite moments of all orders and may have a bimodal distribution. In practice, the reduced form equation (1) must be estimated. Least squares (LS) may not be strictly appropriate, however, because the reduced-form disturbance is potentially serially correlated and the regressors include lagged dependent variables (O_{t-1}) . However, LS has nevertheless been used regularly in the applied agricultural economics literature. Therefore, the authors propose an alternative minimumexpected-loss (MELO) estimator, establish its improved sample properties, and argue for its usefulness in the empirical analysis of agricultural supply response. For small samples the performance of the LS estimator is expected to be poor and the MELO estimator is expected to yield the most improvement. Note that small samples are typical for the estimation of agricultural supply response, where generally only one data point per year is available. As expected, however, the advantage of the MELO estimator decreases as sample size increases (Diebold and Lamb, 1997). The study of Poonyth et al. (1998) recognizes indeed that ordinary LS estimations will not yield reliable estimates because of the presence of serial autocorrelation created by the lagged values of dependent variables. Therefore, Maximum Likelihood (MLE) or instrumental variable estimation methods have been used, which yield estimates with the desired properties.

Jongeneel (1997) proposes an alternative methodology, based on mixed estimation, for efficiently estimating producer supply responses for the EU arable sector. 'Efficiency' and 'mixed' mean making use of all available relevant information in the inference procedure. His estimation procedure allows for the incorporation of economic theory, time series or sample data, and quantitative prior information from previous economic research, or from other disciplines (e.g. agronomics).

Agronomic research has given information about the biological technical progress and the relationship between input use and output yields. When estimating a model on aggregated time series data, the other available relevant information should be used to 'enrich' the estimation procedure. This requires that prior information used should be made clear from the outset. Since there is a lot of information, usually from different sources, the researcher inevitably has to make his own judgment about this. The advantage of this procedure is, however, that these subjective judgements are clearly specified and accounted for, which means they are open for debate. This contrasts with the more classical procedure, which besides accounting for economic theory in a more or less systematic way, focuses particularly on sample data. The author combines the sample information with both 'qualitative' and 'quantitative' information. The first covers theoretical restrictions like homogeneity, convexity and symmetry of the underlying profit function, while the latter is quantitative prior information available from previous (non-)economic research. Quantitative prior information is available either in a rather exact form or only in a vague form.

If there are only some subjective beliefs about the range in which a coefficient is expected to lie, this has to be transformed into prior information suitable for incorporation into the original model. The way to perform this 'translation' is by interpreting the vague prior as a confidence interval. The information is partly derived from other studies and partly created on the basis of external information on yields and biological technical progress. The added quantitative and theoretical prior information significantly influence the ultimately obtained results. While the added restrictions improve the plausibility and reliability of individual coefficients, they reduce the goodness-of-fit, as measured by the individual equation's R².

It seems that estimation of supply response suffers from some important handicaps: (1) serial autocorrelation of the reduced-form disturbance due to lagged dependent variables in the regression equation, and (2) small sample sizes. Diebold and Lamb (1997) attempt tackling the former econometrically by proposing an improved estimator, while Jongeneel (1997) emphasises the inclusion of prior information. A valid alternative approach for the latter is to consider it as an ill-posed problem and apply the maximum entropy formalism, proposed by Paris and Howitt (1998). Their methodology is especially suited to provide a robust answer to these questions since it makes use of all the available information at the farm level, which can be aggregated easily into regional and sector levels. However, their framework still requires prior subjective information (cfr. supra), a weakness that potentially can be overcome with the new set of Leuven estimators (Paris, 2001).

Finally, estimation of supply response can be hampered by the presence of government policies that distort output and input prices. Some of these government interventions are embedded in the Common Agricultural Policy (CAP) of the EU. To illustrate the influence of distorting market policies on the estimation of supply response, Figure 4 represents the quota system of the European common sugar market. This Common Market Organisation (CMO) is central in the case study of herbicide tolerant sugar beets. The quota system is in place since the establishment of the CAP for sugar in 1968. Each year the EU fixes an intervention price P_i from which it deduces the price levels of A-quota (P_a) and B-quota (P_b). To each country an amount of A-quota (P_a) and B-quota (P_a) is allocated. Historically, anticipating an increase in consumption, these quotas have been fixed at a level, which is superior to domestic demand P_a (Combette, Giraud-Heraud, and Réquillart, 1997), the quantity

demanded at a price P_i , defined by the intersection of the demand curve (D) with the fixed intervention price P_i . The production of C-sugar is not limited but it receives the world price (P_w) , without price support.

Now consider two producing countries, characterised by supply or marginal cost functions S_0 and S'_0 . The marginal return curve (abcdef) is stepwise with a discontinuity at b and d. S_0 represents a high cost producer since it fulfils its A- and B-quota (his marginal cost curve S_{θ} intersects with the marginal return curve at Q_a + Q_b), but is too expensive to produce any C-quota (P_w is lower than the intersection of marginal cost and return). S'_{θ} is the marginal cost curve of a low cost producer, who is able to supply an amount of unsubsidised C-sugar (Q_c) , after fulfilment of his Aand B-quota. In their production decisions, EU sugarbeet producers consider both market and policy factors. For most producers, the price received for A- and B-sugar is sufficient to cover marginal production costs (S_0) , so producers generally will produce enough sugar to fill their quota. For producers with marginal production costs between the prices received for B-sugar and C-sugar, the desired production levels should equal the sum of A-sugar and B-sugar quotas. On the other hand, producers whose marginal costs are equal to the C-sugar price (P_w) , will first fulfil the A- and B- sugar production quotas and then will produce above quota C-sugar. For producers that consistently produce C-sugar, this implies that the world price is the producer incentive price, since producers receive the world price for a marginal unit of production. Therefore, for C-sugar producing producers the elasticities calculated by Poonyth et al. (2000) are based on the world price as the incentive price, while for the other producers, the incentive price is a weighted average of A-sugar and B-sugar prices (Table 4).

Since 1968, quota and prices have not changed dramatically. As a result, quota and price levels do not show a large variation during the last thirty years, hampering any econometrical estimation of supply response. If the marginal cost curve for a typical producer would correspond to S_0 , then the expected coefficient on the price term would be close to zero, like in the case of Belgium, Denmark, Spain, Italy, Austria, Finland, and Sweden (Table 4). On the other hand, if the marginal cost curve of a typical producer would correspond to S'_0 , then the quota coefficient should be close to zero as marginal production decisions should be unaffected by small changes in the quota. If a country has some producers with marginal cost curves similar to S_0 , and others with marginal cost curves like S'_0 , then both quota levels and sugarbeet prices should have significant impacts on production (Poonyth, 1998), like in the case of Belgium, Denmark, France, Germany, The Netherlands, and the UK (Table 4).

Now, consider a technological innovation represented by a parallel shift of the supply curve (from S_0 to S_l) by an absolute cost reduction of K (in Euro/tonne). The total producer benefits of this innovation are $K(Q_a + Q_b)$, visualized by the shaded rectangle. Since prices and quota are fixed, no direct price effect will occur on the domestic market as a consequence of the technological innovation. In a free market, increased supply due to the innovation would result in lower prices if the farm sector faces an inelastic demand. Therefore, within quota production is entirely protected from any technology-induced price depreciation. The producers capture the full benefits in the output market, while no benefits flow to consumers. A low cost producer (S'_0) will gain a 'protected' quota rent increase $K'(Q_a + Q_b)$ from his A- and B-quota sugar, equivalent to high cost producers. Moreover, he will capture an extra

benefit on the export market originating from his C-sugar. This benefit, however, is not protected from price depreciation, so it will be less than $K'Q_c$.

The important implication for our analysis is that research benefits for within quota production are more or less²¹ independent of the magnitude of the supply response elasticity, since in our model in Figure 4 the area $K(Q_a + Q_b)$ does not depend on the slope of the supply curves. This concretely means that no estimates of supply elasticities have to be found for high cost producing countries (not producing any significant amount of C-sugar). For C-sugar producing countries at the other hand, the magnitude of the supply response elasticity has a direct influence on the price depreciation on the world market, due to technological innovation, and hence on the out-of-quota research benefits $K'Q_c$. From this example it becomes apparent that the specific institutional policies intervening in the commodity market shape profoundly the model, its underlying parameters and the results. An important conclusion is that there will not exist a unique simulation model for all agbiotech case studies, since it has to be adapted to the specific features of the Common Market Organisation (CMO) of each commodity being modelled.

Chaos

World prices for sugar are remarkably volatile. In a recent article, Bourges (1998) reports sugar price volatility indices that are three to six times higher than these of raw materials, maize and wheat during the period 1962-1989. In an attempt to validate a provisional version of a model of the world sugar industry, Boussard and Piketty (2000) show that sugar prices are inherently highly unstable. The authors offer two possible explanations for this phenomenon. First, the 'cobweb theorem'

explanation advances that there exist situations, especially those deriving from low demand elasticity²², where markets may not tend towards equilibrium. Rather, prices fluctuate wildly, loosing their ability to provide reliable information between producers and consumers. Instead, they generate risk, which is not neutral toward production, since it leads producers to be cautious and to reduce investment and production. The second explanation for volatility of commodity prices departs from the observation that the market is subject to random disturbances due to meteorological or similar causes. These should in principle be damped out over the course of time. However, because the sugar market is far from being 'free', these shocks, instead of being absorbed by a large pool of consumers are amplified by the behaviour of regulated economies which, in one way or another, provide a price guarantee for their producers, thus distorting markets when unexpected temporary overproduction is spilled into a narrow market. During the validation process, the authors discover that the outcome of their model is chaotic, which means that residuals are not independent of time and will logically grow to infinity. They advance this specificity of chaotic series as one of the reasons why so many excellent econometric sugar models have performed so poorly in the past.

What is the link between volatility of the world sugar price and our welfare analysis of agricultural biotechnology in the EU? One of our case studies is the economic impact of herbicide tolerant sugarbeets in the EU. At the center of the analysis is the calculation of a counterfactual world sugar price (after decline) to isolate the effect of the technology-induced supply shift from other exogenous changes in supply and demand (Demont and Tollens, 2001b). It is important to note that this price change would differ from the observed change in world price if the technology had been

adopted as assumed. It rather represents what the world price would have been if all supply and demand conditions had been identical except for the introduction of the new technology (Falck-Zepeda, Traxler, and Nelson, 2000b). Since the core of the analysis finally consists in an *equilibrium displacement model*²³ (EDM), one could question the value of this model in a situation where the world sugar price is highly volatile *without* tending towards equilibrium.

However, despite the fact that sugar prices have been highly volatile in the period from 1970 to 1987, confirming the chaos theory of Boussard and Piketty (2000), Hannah (1999) offers three arguments that in the decade 1988-1998 the world sugar price reached an equilibrium range of 9 to 13 cents/lb with an average of 11 cents/lb. First, least cost producers (Brazil, Australia and Thailand) all expanded production and exports from 1988 to 1997. Assuming rationality, it is inconceivable that these exporters would have expanded to the extent they did if it had not been profitable to do so. Secondly, the evidence of the 1970's and 1980's suggests that significant expansion of HFCS (High Fructose Corn Syrup), a competitor of sugar, is triggered by high sugar prices. According to the production cost calculations made by LMC (Landell Mills Commodities) International Ltd. (1997), the world average cost of production of HFCS is 14 cents/lb, sugar equivalent. If the world sugar price had settled at a price higher than the production cost of HFCS, it would not have been a maintainable equilibrium. HFCS would have been stimulated, taking market from sugar, and the result would have been overproduction of sweetener and declining sugar prices. Thirdly, further evidence comes from the same production cost calculations showing clearly that sugar price and cane sugar production costs are converging over the period.

Our strategy of assessing the welfare effects of transgenic sugarbeets in the EU consists in assuming hypothetically²⁴ that the EU's sugar industry, as a competitive player in the world market, embraced the new technology of herbicide tolerant sugarbeets since the marketing year 1996-1997 (Demont and Tollens, 2001b). This setting implies that the new technology is being introduced at a moment when world sugar prices are in equilibrium, according to the arguments of Hannah (1999) and that the use of an equilibrium displacement model, as proposed, is justified. Hence, our model will produce reliable estimates of the counterfactual world price, as a result of a displacement of the equilibrium world price, and of the welfare effects of transgenic sugarbeets in the EU and the rest of the world.

Modelling Uncertainties

Objective versus Subjective Estimates

Data, whether they have been estimated based on available real world information or provided by experts, always contain an uncertainty component. Two types of data can be distinguished entering our modelling approach:

- Objective estimates about existing facts or events: demand and supply elasticities, current prices and quantities, and production costs;
- Subjective estimates about 'immeasurable' current or future events: farm level impacts, adoption rates and technology prices.

The main difference between the two is that objective estimates can be checked for validity, while subjective estimates are not subject to validation. When discussing subjective estimates, it is more common to refer to 'performance' than to validity (Fishel, 1985). For a discussion on this rather involved topic, we refer to Linstone

and Turoff (1975). But even when objective estimates can be validated, they are still subject to uncertainty due to measurement problems (e.g. supply and demand elasticities, cfr. supra), lack of data and small sample sizes (e.g. production costs). Therefore, not only the most likely value of a parameter has to be incorporated into welfare calculation models, but also its uncertainty.

Already in the mid eighties, a decade before the adoption of the current wave of agricultural biotechnology innovations, Fishel (1985) expressed concern about the adequacy of conventional analytical techniques to examine the impact of modern agricultural biotechnology. He even advanced the need to reexamine the philosophical conceptualisation about how technology assessment studies of biotechnology are considered and contends that there must be some analytical extensions to these methodologies in order to generate the kind of information that is going to be required by decision and policy makers. Today with the introduction of agricultural biotechnology, literature has indeed provided some analytical extensions to the conventional models, reviewed by Demont and Tollens (2001a) in a recent paper.

In this section, we depart from Fishel's reflections about the concept of precision and the key role of uncertainty as an element of information equal in importance to the *ex ante* impacts we want to assess:

... many of the events in which we are interested have not happened yet, so neither have the measures of those events. Consequently, I am convinced that we, out of necessity, are going to have to rely more and more on "expert" opinion ... what I am talking about is a greater role in the use of subjective estimates. ... data obtained by

subjective estimation is still looked on as a second class method of data collection. ...

This is regrettable, because it prevents our recognising that, beyond a necessary thing to do, subjective estimation techniques can be in their own right a relatively powerful tool (Fishel, 1985, pp. 10-11).

Different techniques have been developed in order to meet the increasing demand for subjective estimates in science. The potential use of these techniques in biotechnology impact studies has been reviewed by Tollens (1985). Starting in the late 1950's, techniques such as Critical Path Method (CPM) and the Program Evaluation and Review Technique (PERT) made subjective estimation legitimate (Moder and Phillips, 1970). First, the PERT system, adapted²⁵ by Moder and Phillips (1970), is based on three subjective estimates: (1) the optimistic value, occurring one time in twenty, (2) the most likely value, and the (3) pessimistic value, occurring one time in twenty. These three estimates allow fitting of a beta distribution curve, which can be used in statistical methods. Secondly, Fishel (1985) developed a similar method called 'impression measurement', in which five estimates are requested for a variable: the two 100 % certainty limits, the two 67 % certainty limits, and the most likely estimate. Analogous to PERT, a unique beta distribution is estimated based on these five estimates.

Finally, the Delphi method is a systematic iterative process, in which a questionnaire is sent to a respondent group of experts. After the questionnaire is returned, the monitor team summarizes the results and, based upon the results, develops a new questionnaire for the respondent group. The respondent group is usually given at least one opportunity to re-evaluate its original answers based upon examination of the

group response. Usually Delphi undergoes four distinct phases. The first phase is characterised by exploration of the subject, wherein each individual contributes additional information he feels is pertinent to the issue. The second phase involves the process of reaching an understanding of how the group views the issue. If there is significant disagreement, then that disagreement is explored in the third phase to bring out the underlying reasons for the differences and possibly to evaluate them. The last phase, a final evaluation, occurs when all previously gathered information has been initially analysed and the evaluations have been fed back for consideration (Linstone and Turoff, 1975). Obviously, the first two methods can be integrated in a Delphi process in order to generate a reliable idea about the most likely value of a parameter and its distribution.

In our modelling approach, subjective estimates about 'immeasurable' future events can be classified into two groups:

- Controlled subjective estimates, since they are under the control of decision makers, such as the price of the new technology;
- Not-controlled subjective estimates, such as farm level impacts and adoption rates.

The first group of estimates including technology fees and price premiums are especially eligible for a Delphi method, in which experts like decision makers are confronted with different opinions and the effect of different decisions. To assess the second group of estimates, expert opinions (e.g. for adoption rates) can be used as well as objective estimates. In the latter case, objective estimates (e.g. field trial results) are extrapolated to approximate subjective estimates about 'immeasurable' future events (e.g. farm level impacts).

Sensitivity Analysis (SA)

When parameter values and assumptions of an economic model are subject to error and uncertainty, sensitivity analysis (SA) allows investigating these errors and uncertainties and their impacts on conclusions to be drawn from the model. Pannell (1997) observes that, despite its usefulness in applied economics, SA has been largely neglected in the entire discipline of economics. There has been hardly any discussion of methodological issues for SA in economic models. The author provides an extensive review and overview of theoretical and methodological issues, different approaches and overall strategies in SA. A common characteristic of the methods presented however, is that they do not require the modeller to explicitly specify probabilities of different situations. Moreover, the paper is somewhat focused on decision support, while our modelling approach is rather centred on aggregate impact estimation, which is not completely under control of decision makers.

A shortcoming of equilibrium displacement models (EDM) is the assumption that the structural parameters (elasticities) are known with certainty. To overcome this deficiency, a common practice is to present a table showing some alternative values of the structural elasticities and the resulting alternative values of the outcomes of the simulation model, like in the seminal article of Gardner (1975). This procedure is the equivalent to generating a few points from the unknown conditional distributions for the outcomes, without providing any information about their most likely values, though. Therefore, arguing that one of the major shortcomings of EDM's is the way in which SA is conducted, Davis and Espinoza (1998) propose a more unified and informative approach. They propose to include the researcher's entire subjective prior distributions on the structural elasticities, and not just the expected values as point

estimates. Sampling techniques, like Monte Carlo simulation or Latin Hypercube, then can be used to generate posterior distributions for the outcomes of the simulation model. Measures of central tendencies and dispersion can be easily calculated from the generated posterior distributions, as well as confidence intervals, p-values, and hypothesis tests. In the literature on the welfare effects of agbiotech, the above mentioned *stochastic equilibrium displacement model* (SEDM) has been adopted²⁶ by Falk-Zepeda, Traxler, and Nelson (2000b), and Price, Lin, and Falck-Zepeda (2001).

For our case studies, our modelling strategy will apply this methodology in two distinct phases:

- First phase: definition and introduction of prior distributions for all uncertain or subjective parameter estimates in the model and simulation of the posterior distribution of the outcomes;
- Second phase: narrowing down the distribution of the subjective parameter estimates by an increasing reliance on expert opinions via Delphi methods, starting with the parameters for which the outcomes of the model are the most sensitive.

Obviously, using economic theory and other prior information, the distributions of certain parameters can already be narrowed down in the first phase. Distributions of supply and demand elasticities for example can be truncated and limited to the appropriate theoretical range, i.e. respectively the positive and the negative portion of the real line. In addition, previous estimates of an elasticity reported in the literature can be used to further restrict the range and shape of the prior distribution on an elasticity. The key is that the distributions and their parameterizations should be chosen so that the resulting prior destributions accurately reflect the researcher priors.

It is clear that the above-presented methodology is fundamentally different from a conventional econometric model:

In an econometric model, the unrestricted estimation process forces the parameter estimates and the data set under consideration to be compatible. Hopefully, the parameter estimates are then also compatible with the theory. Alternatively, in an equilibrium displacement model, the researcher forces the parameter estimates and the theory to be compatible (Davis and Espinoza, 1998, p. 878). ... EDM's are best suited for situations where data are insufficient for a complete econometric analysis and if data are sufficient for a complete econometric analysis, an EDM should not and would not be used in practice (Davis, 2001, p. 2).

Model Validation

One of the most important principles in any science is testing and consequently confirmation and falsification. The EDM however, is presently not testable and cannot be confirmed or falsified. The accuracy and validity of the EDM approach clearly rest on two maintained assumptions. First, the structural parameter estimates are considered unbiased or at least reasonable. Second, the structural model is taken as being true or correct. The work of Davis and Espinoza (1998, 2000) and Griffiths and Zhao (2000) concentrates on the first maintained assumption (cfr. supra) by introducing the concept of stochastic equilibrium displacement model (SEDM). While the SEDM is certainly an improvement over previous attempts to allow for parameter uncertainty, the truth of the underlying structural model is still a maintained assumption. Therefore, Davis (2001) presents four procedures designed to overcome this significant limitation by making them confirmable or falsifiable without completely destroying their major advantage, which is ease in implementation.

In an equilibrium displacement model, market clearing or market equilibrium is forced through equating supply and demand functions. Solving this system of simultaneous equations yields two *reduced form* equations: a reduced form price and a reduced form quantity. The *unrestricted reduced form estimator* comes from just econometrically estimating the reduced form equation, without imposing any of the overidentifying restrictions stemming from the defined prior parameter distributions. The *restricted reduced form estimator* comes from substituting the prior structural parameters being utilized in the SEDM into the overidentifying restrictions. If the SEDM restrictions are 'true' then there will be no statistical difference between the unrestricted estimate and the restricted estimate. Alternatively, if the restrictions are not 'true' then the unrestricted estimate and the restricted estimate will be statistically different. In this context, the unrestricted reduced form model is to be interpreted only as a testing model, not necessarily a descriptive model.

The attractive feature of this methodology is that data on all the endogenous variables are not needed. Data on one endogenous variable is sufficient and, for most commodities, the obvious candidate is the price. By comparing the restricted reduced form (i.e. the EDM result) with the unrestricted reduced form, Davis (2001) presents four increasingly sophisticated methods to confirm or falsify EDM models. These procedures can also be applied on *ex ante* equilibrium displacement models, and hence on our modelling framework (Davis, 2001, personal communication).

EUWABSIM

Our theoretical stochastic simulation model is materialised in the software package 'EUWABSIM' (European Union Welfare effects of Agricultural Biotechnology Simulation Model). This package is the unique combination of three interlinked modules: a Microsoft Excel 2000 module, a Mathcad 2000 module, and an @Risk 4.0 module. The originality and uniqueness of this combination of software packages lies in the interaction between the different modules (Figure 6). First, data on parameters coming from the literature, expert opinions and economic theory are stored in an Excel file, which is the base module of the package. Secondly, these data are sent to the Mathcad module. The mathematical software program Mathcad, an add-in for Excel, enables to present and calculate the mathematical model in a formal way, including functions that are not incorporated in Excel, such as the calculation of integrals (Mathsoft Inc., 1999a, Mathsoft Inc., 1999b). As a result, this mathematical module contains the mathematical body of the model. The Mathcad module uses the data from Excel to calculate the outcomes of the model. These outcomes are then returned to Excel. Thirdly the computer program @Risk, also an add-in for Microsoft Excel, enables introducing prior distributions for parameters in the individual cells of an Excel sheet (Palisade Corporation, 2000). Hence, this uncertainty module allows incorporating and analysing all uncertainty elements of the model. For all parameters, @Risk randomly picks values from the defined prior distributions and sends them to the data cells in Excel. Each time the data values are changed in Excel is called an iteration²⁷. For each iteration, Mathcad recalculates the model and sends the outcomes to Excel. @Risk then collects all different values, generated by each single iteration, in a file. This finally allows the program to generate posterior distributions, statistical analyses, and sensitivity and scenario analyses for the model outcomes.

Conclusions

In the literature, impact estimates of agricultural biotechnology vary strongly according to the region, the crop, the time, the scale, and the methodology of the study. Therefore, this paper provides a methodological background for analysing, interpreting, and comparing these estimates. In the literature and the popular press, a large diversity of impact estimates is quoted. However, the paper shows that there exist a hierarchy in estimation procedures. As a result, some estimates may be biased and should be interpreted accordingly. The presence of this diversity in impact estimates is partially due to the existence of uncertainties. Some uncertainties may be due to methodological issues in the calculation of research benefits, while others are specifically related to the new technologies themselves. Given this large set of uncertainties, one may question whether estimating the welfare effects of agricultural biotechnology in the European Union is feasible at all, before even the new technology has been adopted. To answer this question, we agree with Fishel (1985, pp. 5-6) that:

... issues related both to management decisions and to governmental adjustment programs will need to be anticipatory rather than reactive. ... can we wean ourselves away from the overwhelming preoccupation with precision in our analysis? Can we adjust ourselves to a "looser" form of analysis that is designed to help anticipate change rather than understand it?

Taking 'anticipation' as our primary study objective, our modelling framework can be continuously updated with new information from experts, ore even from the first biotechnology adoption experiences in the European Union. However, 'completeness' should be our second study objective, accomplished through extensive sensitivity²⁸ and scenario analyses.

Table 1 : Potential Bias in Measured Economic Impact

		Transgenic Trait			
Type of Trial		Pesticide-tolerant	Pesticide-inheren		
1.	Laboratory Trial	+/-	+/-		
2.	Yield Trial, Currently Used	-	-		
	Conventional vs. Transgenic				
	Yield Trial, Near-isogenic Lines	+	+		
	Pest Control Trial	+/-	-		
3.	On-farm Partial Adoption Trials	-	0		
4.	On-farm Field-level Surveys	+/-	+/-		
5.	Whole-farm Surveys	0	0		

(Marra, 2001)

Table 2: Impact of Adopting Bt Cotton in the Southern Seaboard of the US on Crop Yields and Pest Control Costs by Data Source in 1997

Item		Data Source			
	Means of ARMS	Elasticity-based	EMD		
Crop Yield	+ 11,6 %	+ 21,0 %	+ 11,3 %		
Pest Control Costs	- 5,27 %	- 7,08 %	- 60,0 %		

(Lin, Price, and Fernandez-Cornejo, 2001)

Table 3: Total Farm Budget of an Average Sugarbeet Grower in the UK

Category		CPI 300 Average
	Adjusted Yield (t/ha)	59,70
	Average Beet Price (£/t)	25,96
Total Output		1549,76
Variable Costs (£/ha)	Seed	99,11
	Fertiliser	89,40
	Organic Manure/Lime	16,33
	Herbicides	115,70
	Insecticides	36,29
	Fungicides	7,75
	Foliar Feeds	4,84
Total Variable Costs (£/ha)		369,42
Gross Margin (£/ha)		1180,34
Operational Costs (£/ha)	Primary Cultivations	40,16
	Other Cultivations	25,63
	Drilling	27,96
	Fertiliser Applications	16,90
	Chemical Applications	33,78
	Tractor Hoeing	10,64
	Irrigation	6,06
	Other	5,59
	Harvesting	149,25
	Delivery	238,57
Total Operational Costs (£/ha)		554,53
Other Overheads (£/ha)		100,00
Total Costs (£/ha)		1023,95
Unit Costs (£/ha)		17,15
Enterprise Margin (£/ha)		525,80

(Limb, 2000)

Table 4: Area Harvested Equations of the European Union Sugarbeet Sector

	Consta	A_{t-1}	P	Quota	P_c	Trend	R^2	DH
	nt							
Belgium	14,814	0,415	0,035	0,453	-	-	0,94	0,238
Denmark	14,148	0,633	0,045	0,153	-	-	0,96	1,422
France	50,895	0,320	2,987	0,664	-3,325	-	0,95	0,621
Germany	71,696	0,492	3,042	0,321	-7,098	-	0,99	0,893
The Netherlands	48,048	0,440	0,483	0,162	-	-	0,65	0,864
Spain	23,003	0,649	0,048	-	-	-	0,71	1,562
UK	21,797	0,663	3,677	0,200	-7,238	-	0,94	1,243
Italy	33,376	0,369	0,016	-	-	-	0,70	0,200
Ireland	13,219	0,576	0,136	-	-	-	0,91	1,388
Austria	17,169	0,603	0,079	-	-	-	0,77	1,366
Finland	2,753	0,723	0,040	-	-	2,117	0,81	1,346
Sweden	10,034	0,447	0,043	-	-	5,600	0,92	1,036

(Poonyth et al., 2000)

Table 5: US Welfare Effects of Adopting Bt Cotton in 1997 by Data Source

	Mean of ARMS		Elasticity-based		EMD	
Stakeholder	$10^6 \mathrm{USD}$	%	10 ⁶ USD	%	10 ⁶ USD	%
U.S. Farmer Surplus	31,4	22,4	78,2	36,2	132,1	46,4
U.S. Consumer Surplus	9,9	7,1	19,9	9,2	30,9	10,8
Monsanto	62,0	44,2	62,0	28,7	62,0	21,8
Delta & Pine Land	12,9	9,2	12,9	6,0	12,9	4,5
ROW Producer Surplus	-35,8		-77,8		-132,3	
ROW Consumer Surplus	59,8		120,7		179,3	
Net ROW	24,0	17,1	42,9	19,9	47,0	16,5
Total World Surplus	140,2		215,9		284,9	

(Price, Lin, and Falck-Zepeda, 2001)

ROW = Rest of the World

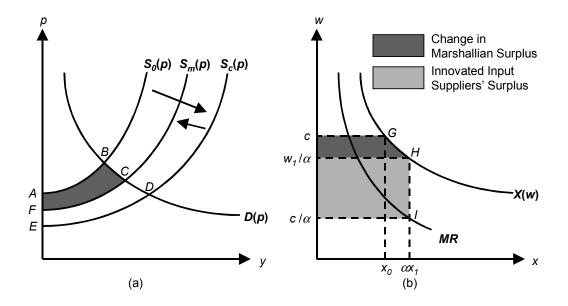


Figure 1: Change in Marshallian Surplus (area ABCF or $cGHw_1/\alpha$) and Innovated Input Suppliers' Surplus (area $w_1/\alpha HIc/\alpha$) Resulting from an IPR-Protected Innovation in the Input Market (Moschini and Lapan, 1997)

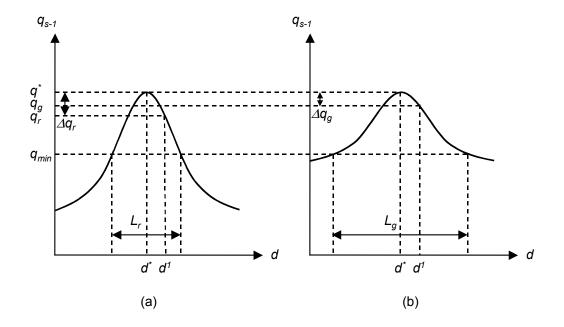


Figure 2: Change in Task Flexibility Due to Agricultural Biotechnology Innovations

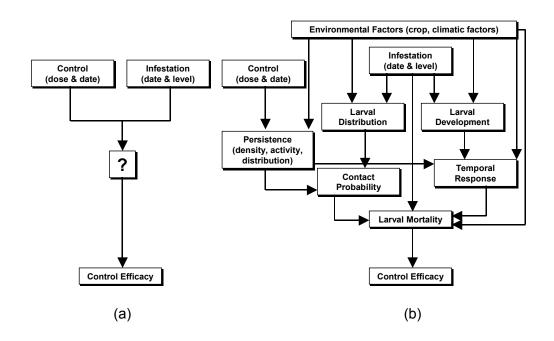


Figure 3: Diagrams Showing the Conventional Study of Pest Control Impact and the Proposed Study (Labatte et al., 1996)

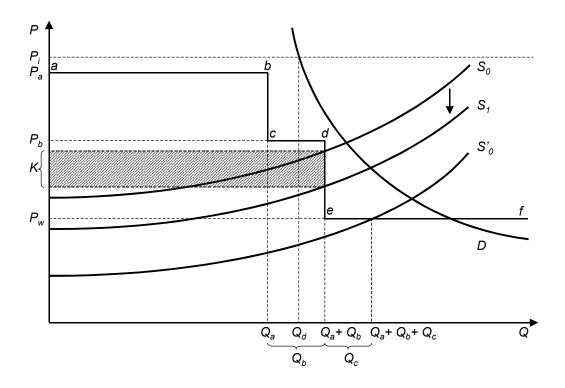


Figure 4: Quota System of the European Common Sugar Market

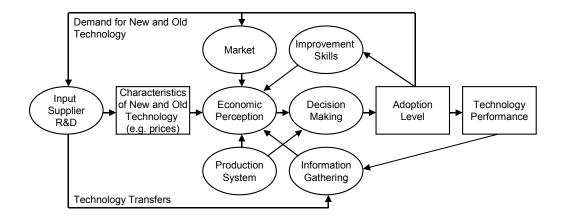


Figure 5: Mental Image of the Technology Adoption Process (adapted according to Hebert and Goldsmith (2000))

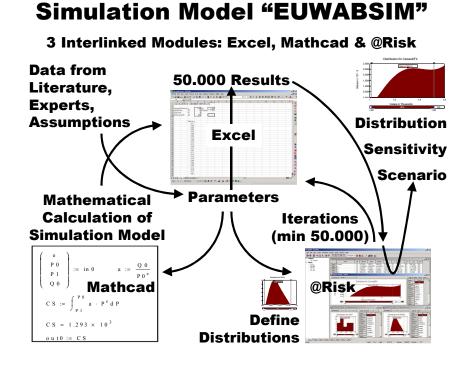


Figure 6: Schematical Representation of the Simulation Model 'EUWABSIM'

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¹ For a comprehensive overview of field trials taken place since 1986 in OECD countries, we refer to the OECD's database of field trials which is online accessible through http://www.olis.oecd.org/biotrack.nsf. You can make your own field trial table and search or browse the database, by country, or by organism. Summaries of the data are also available (OECD, 2001).

- ² Pesticide-inherent crops have a pesticide genetically inserted into the seed, such as the Bt crops (corn, cotton, potatoes and soybeans).
- ³ Near-isogenic varieties are nearly identical in terms of their genetic makeup, except for the insertion of a specific gene or trait.
- ⁴ These data have been obtained from a survey of consultants conducted by Plexus Marketing Group, Inc. and Timber Mill Research, Inc. In this survey, cotton consultants were recruited to provide agronomic and pest management information on matched pairs of Bt and non-Bt cotton fields. These matched pairs of fields were carefully selected so that they represented equivalent histories of crop production, agronomic practices and productivity. Data were included for fields in Alabama, Arkansas, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, and East Texas.
- ⁵ An interesting study related to this topic can be found in the paper of Fernandez-Cornejo, Daberkow, and McBride (2001), who examine the relationship between farm size and the adoption of agricultural biotechnology. Their results show that the adoption of herbicide tolerant soybeans is invariant to farm size (scale-neutral), while for Bt and herbicide tolerant corn, adoption seems to be biased towards larger farm operations. However, the latter could be due to the fact that their 1998 sample only included the innovaters and early adopters who in general tend to control substantial resources.

⁶ a Canadian oilseed rape variety

⁷ Benbrook (1999) found similar evidence of this yield drag for herbicide tolerant soybeans.

⁸ This article has its origine on the 2000 Annual Meeting of the American Agricultural Economists Association. Matty Demont initiated a conversation with Terrance M. Hurley and Paul D. Mitchell about the potential risks effects of Bt corn, by referring to the articles of Horowitz and Lichtenberg (1994) and Carpentier and Weaver (1997), and suggested that Bt corn could possibly increase risk, instead of decreasing it as conventionally assumed. This discussion would have encouraged the authors to initiate an empirical study on the risk effects of Bt corn (Mitchell, personal communication).

⁹ For a more aggregate analysis on the influence of climat and technological change on the risk in corn production, we refer to the study of Kim and Chavas (2001). Using time series data (1974-1997) from several research stations in Wisconsin, they econometrically examine the effects of technological change on the mean, variance and skewness of corn yield and corn profitability, as they evolve under technological progress. Their empirical results indicate that technological progress contributes to reducing the exposure to risk as well as downside risk in corn production. They also stress the role of the relative maturity of corn hybrid as a means of managing risk.

- ¹² The authors believe that biological as well as chemical innovations, such as agricultural biotechnology, result in a divergent shift, while mechanical and organisational innovations are scale dependent and result in a convergent shift of the supply function.
- ¹³ One exception is the case of a yield-increasing innovation, which does not require input changes per unit of land (Hicks neutral technical change), likely resulting in a divergent supply shift.
- 14 (.) refers to a price or quantity variable and Δ implies the finite change of the variable
- ¹⁵ Consumer surplus, as defined by Marshall (1890), is the excess of the price the consumer would be willing to pay over the actual cost of the good.
- ¹⁶ Producer surplus is the excess of the return to the factor owner above that necessary to induce him or her to provide the factor, and it is analogous to the concept of consumer surplus (Mishan, 1968).
- ¹⁷ Equivalent variation, a concept defined by Hicks (1948), is the amount of additional money (income) that would leave the consumer in the new welfare position if it were possible to buy any quantity of the commodity at the old price.
- ¹⁸ Compensating variation is the amount of additional money (income) that would leave the consumer in the initial welfare position if it were possible to buy any quantity of the commodity at the new price.
- ¹⁹ For a more detailed review on the issues and uncertainties in the estimation of on-farm benefits of agricultural research and on how a constructive dialogue with scientists can be achieved, we refer to an interesting methodological paper of Pannell (1999).

¹⁰ The recent findings of Hurley, Mitchell and Rice (2001) however, show that the opposite can occur too, like in the case of Bt corn (cfr. supra).

¹¹ This idea originated during his stay in Leuven in March 2001.

²⁰ A partial equilibrium approach only takes into account the agricultural market, while a general equilibrium model includes all related markets surrounding the agricultural sector.

- ²¹ This depends on the functional form used for the supply functions, but even then, supply elasticities have no major influence on price-protected within-quota research benefits.
- According to Hannah (1999), developed countries have very low or zero price elasticities for sugar. This means when supplies are short (and prices high) they try to purchase their requirements, driving the price even higher. Developing countries, on the other hand, have higher price elasticities, purchasing more when prices are low and less when prices are high. Developing countries have therefore a stabilising influence on the market, whereas developed countries destabilise the market.
- ²³ The equilibrium displacement model originated with Muth (1964) and is one of the most frquently used tools in agricultural economics (Davis and Espinoza, 1998).
- As we mentioned earlier, this strategy reveals the *benefits foregone* or costs of the current moratorium on GMO's in the EU, and more specifically on transgenic sugarbeets.
- ²⁵ The original development of PERT used the ultimate limits, or the 0 and 100 percentiles of the distribution of the variable.
- ²⁶ Moschini, Lapan and Sobolevski (2000) on the other hand, apply a conventional way of doing SA. They recalculate their model for some alternative values of the structural elasticities, relative to a benchmark, without introducing any subjective prior distributions of the structural parameters.
- ²⁷ The number of iterations can be chosen arbitrarily in @Risk. However, the more iterations, the more detailed are the estimates of the posterior distributions. The iteration process can be automatically stopped when convergence of the model results is attained.
- In an *ex post* analysis roughly 50 % of the time is spent on data collection, 25 % on modelling and 25 % on sensitivity analyses. In an *ex ante* analyses, lack of adoption data limits the data collection phase to 25 % of the research time. Assumptions, hypotheses, expert opinions, and economic theory are also considered as data. Since both methodologies use essentially the same modelling frameworks, an equal proportion (25 %) of the time is devoted to modelling. Finally, in an *ex ante* analysis, 50 % of the time is spent on sensitivity analysis to assess the sensitivity of the results to the parameter values and assumptions made in the analysis. Note that even in an *ex post* setting, sensitivity analysis is important, due to measurement problems in the estimation of the model parameters.

List of Available Working Papers

- nr. 1 BEERLANDT, H. en L. DRIESEN, *Criteria ter evaluatie van 'duurzame landbouw'*, Afdeling Landbouweconomie, K.U.Leuven, januari 1994, 35 p.
- nr. 2 BEERLANDT, H. en L. DRIESEN, *Evaluatie van herbicide-resistente planten aan criteria voor duurzame landbouw*, Afdeling Landbouweconomie, K.U.Leuven, januari 1994, 39 p.
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