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Raw Material Supply Estimation Lessons from the Non-food Industry: A Mathematical Programming Approach[1]

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3.1 INTRODUCTION

Raw material cost reaches a considerable part of agro-industry chains products. This note focuses on the raw material cost estimation in the bio-energy industry, that in some cases amounts at 60% of bio-fuel cost for bio-chains. Therefore biomass supply curve estimation is extremely valuable for the industry as well as for governmental agencies. This paper attempts to estimate energy crop supply based on mathematical programming principles. In order to enhance the predictive ability of such a model and to provide an analytical tool useful to policy makers, interval linear programming (ILP) is used to formalise bounded rationality conditions. In the presence of uncertainty related to yields and prices it is assumed that the farmer minimises the distance from optimality once uncertainty resolves introducing an alternative criterion to the classic profit maximisation rationale. Model validation based on observed activity levels suggests that about 40% of farms adopt the min-max regret criterion. Then energy crop supply curves, generated by the min-max regret

1 An extended version of this note to be presented in the tri-annual Congress of the European Association of Agricultural Economists in Copenhaguen, August 2005.

model, are proved to be upward sloped but slightly displaced to the right compared with classic LP supply curves.

The first major Common Agricultural Policy reform of 1992 that shifted support from price to cultivated surface attempted to cope with overproduction and excess stocks of cereals introducing the obligatory Set Aside. This latter measure would have a considerable impact to European cereal produces assessed by numerous studies. This was one of the reasons that pushed the French government to decide to exempt biofuels from the Petroleum Products Excise already in 1993, thus to alleviate pressure on the income of numerous arable cropping farmers, while supporting agro-industry and refineries to exploit patents on biofuels and use idle capacity. An important part of the budget, which reached € 150 million in 2000, is annually earmarked to finance biofuel excise tax exemption, allocated among the Ethyl Tertio Butyl Ether (ETBE) and Rapeseed Methyl Ester (RME) industry and the agricultural sector, namely wheat, sugar-beet and rapeseed producers. This policy has been criticised on efficiency grounds leading the government to revise the unitary tax exemption levels in 2002 at the expense of ethanol chain. Sourie et al. (2002) as well as Sourie and Rozakis (2001), have carried out studies of the French agricultural production of energy crops by means of mathematical programming. These studies reveal that agricultural raw material expenditure constitutes a significant part of the biofuel cost that depends on food crops' profitability. A precise assessment of it would enhance the value of economic analyses on biofuels. This would enable welfare effects to be correctly estimated thus assisting in credible evaluation of public policy.

The above mentioned studies elaborated arable sector linear programming models, comprising hundreds of representative farms, that maximise farm income subject to the interdependencies of food and non-food crops. Different productive units, namely arable cropping farms act independently in a context of perfect competition. Such sector models are built upon a common sort of structure which arises in multi-plant models, known as a block angular structure (Williams, 1999), account for policy changes and can be used to derive opportunity costs and supply curves of energy crops (Sourie, 2002). Mathematical programming has proved to be one of the most powerful tools in the analysis of resource allocation choices at the firm and sector level. However, the introduction of alternative methods to classic linear programming in order to consider risk at the level of the decision making (DM) unit when selecting among alternative activity levels seems necessary in the increasingly uncertain environment of European agriculture. This paper proposes an interval programming approach where the DM (each farmer) has incomplete information on the objective function coefficients at the crop mix decision moment. It is assumed that beside the risk-neutral expected gross margin maximisation behaviour, risk-averse farmers may adopt the min-max regret criterion. Observed crop mix data for each representative DM unit reveal whether the farmer adopts risk averse or neutral behaviour. Therefore sub-models corresponding to risk-neutral farms are always specified as LP whereas those sub-models representing farmers that do not pretend perfect information on gross margins are specified as interval linear programming (ILP).

In the following section uncertainty is introduced with a brief review of the literature devoted to interval programming as well as a formal definition of the Interval Linear Programming (ILP) problem is presented. In the third section the background sector LP model and the estimation of non-food crop opportunity costs per farm as well as methodology for deriving supply curves is presented. Results confirm that many firms (farmers) do not follow the profit maximisation rationale in cases of limited information on expected margins. Finally, supply curves determined from a combination of max profit and min-max regret utility functions, that is generated by the hybrid model will be outlined. Conclusions complete the paper.

3.2 UNCERTAINTY AND INTERVAL PROGRAMMING

In mathematical programming models, the coefficient values are often considered known and fixed in a deterministic way. However, in practical situations, these values are frequently unknown or difficult to establish precisely. Interval Programming (IP) has been proposed as a means of avoiding the resulting modeling difficulties, by proceeding only with simple information on the variation range of the coefficients. Since decisions based on models that ignore variability in objective function coefficients can have devastating consequences, models that can deliver plans that will perform well regardless of future outcomes are appealing. More precisely, an ILP model consists of using parameters whose values can vary within some interval, instead of parameters with fixed values, as is the case in conventional mathematical programming.

In the literature, two distinct attitudes can be observed. The first attitude consists of finding all potentially optimal solutions that the model can return in order to examine the possible evolutions of the system that the model is representing. The methods proposed by Bitran (1980) and Steuer (1989) follow this kind of logic. The second attitude consists of adopting a specific criterion (such as the Hurwicz's criterion, the maxmin gain of Falk, the minmax regret of Savage, etc.) to select a solution among the potentially optimal solutions. Rommelfanger (1989), Ishibuchi and Tanaka (1990), Inuiguchi and Sakawa (1995) and Mausser and Laguna (1998, 1999a, 1999b) proposed different methods with this second perspective.

Minimizing the maximum regret consists of finding a solution which will give the decision maker a satisfaction level as close as possible to the optimal situation (which can only be known as a posteriori), whatever situation occurs in the future. The farmers are faced with a highly unstable economic situation and know that their decisions will result in uncertain gains. It seems reasonable to suppose that they will decide on their surface allocations prudently in order to go through this time of economic instability with minimum loss, while trying to obtain a satisfying profit level. This is precisely the logic underlying the minmax regret criterion; i.e. selection of a robust solution that will give a high satisfaction level whatever happens in the future and that will not cause regret (Loomes and Sugden, 1982). Therefore, we make the hypothesis that the farmers of the considered region adopt the min-max regret criterion to make their surface allocation decisions. The mathematical translation of this hypothesis for the arable sector supply model was to implement the minmax regret solution procedure proposed in the literature (Inuiguchi and Sakawa, 1995, Mausser and Laguna, 1998, 1999a, 1999b).

3.3 MATHEMATICAL MODELLING AND SUPPLY OF RAW MATERIAL

The raw material costs, defined at the farm level, form a significant part of the bio-fuel cost. In the French context, this share varies between 20 and 25 % for wheat or sugar-beet and 60 to 65 % for rapeseed (Sourie & Rozakis, 2001). Due to an important spatial dispersion of bio-fuel raw material in many productive units (farms) and competition between agricultural activities for the use of production factors (land in particular), strongly dependent on the CAP, the cost estimates of these raw materials raise specific problems. Thanks to supply models, based on linear programming, it is possible to correctly estimate these costs, their diversity and finally to aggregate them in order to obtain raw material supply for industry. As a matter of fact, three principal difficulties are faced:

Firstly, the scattering of the resource. Currently, France has more than 50 000 energy crop (wheat, sugar-beet, and rapeseed) producers according to the professional association of oil-seed growers (ONIOL, 2002). In this heterogeneous context, average cost is not a suitable concept.

Secondly, the competition existing between agricultural activities and non-food crops at the farm level. In order to satisfy agronomic constraints when introducing non-food crops, food rotation may be altered. This competition imposes a minimum level of profitability for non-food crops. We cannot consider the food activities and the non-food activities as independent so this implies that the full cost valuation method results, which do not take into account endogenous dependences between crops, may be a misleading indicator to predict farmers' decisions regarding energy crop cultivation.

Finally, the dependence of raw material costs on agricultural policy measures. The changes in agricultural policy, for example, a modification of the obligatory set-aside land rate or of the levels of direct subsidies to crops, affect the opportunity costs.

The microeconomic concepts of supply curve and opportunity cost make possible a solution to these difficulties. These concepts could be elaborated in a satisfactory way by using mathematical programming models, called supply models, based on a representation of farming systems. This approach also leads to an estimate of the agricultural producers' surplus, which is an item of the cost-benefit balance of bio-fuels. It is postulated that the farmers choose among food crops X_c and non-food crops X_d so as to maximize the agricultural income of their farm. Thus, each producer f maximizes gross margin (g). Variables X take their values in a limited feasible area defined by a system of institutional, technical and agronomic constraints.

The opportunity cost is obtained in the following way: Firstly, transforming the coefficients of the non-food cultures in the objective function, by removing the sales component, (thus there remain variable expenses (C_d) + subsidies (S_d)):

$$\max \sum_{f \in F} \sum_{c \in C} g_{c,f} x_{c,f} + \sum_{f \in F} \sum_{d \in D} \left(s_d - c_{d,f} \right) x_{d,f} \tag{1}$$

At the optimum of (1) under constraints, surfaces cultivated by energy crops will be zero. Now consider a production of a minimal quantity q of a crop x_d by setting down the constraint $y_d x_d > q$, where y_d represents the yield of the energy crop d. The objective function will decrease and the model will automatically calculate a result which is interpreted as the cost of the last unit produced to reach the imposed quantity q. It is the opportunity cost estimate. This result is an output of any optimization model under constraints, known as its shadow price equal to the constraint dual value. The opportunity cost will vary according to the produced quantities q, within each farm but also across farms when the constraint applies to all farms ($\bar{Q}_d$ non-negative quantities of non-food resources):

$$\sum_{f \in F} y_{d,f} x_{d,f} \geq \bar{Q}_d \qquad \forall d \in D \tag{2}$$

Thus, the energy crop supply takes into account competition with other non-food as well as food crops in a large number of farms. These results underline the interdependence between arable crops as well as cross-price dependencies. The national model is a set of individual farm models, suitably weighted to obtain a representative image of the farms able to produce non-food cultures. The dual values of the binding constraint (2) give the minimal prices p_d^* that the industry must pay the producers in order to obtain the demanded quantity $\bar{Q}_d$. Non-food crop production is distributed in an optimal way among the various farms f, so that reduction in the objective function value, i.e. the total cost of production, becomes minimum. By increasing the quantity $\bar{Q}_d$, one obtains the corresponding p_d^*. The relation $p_d^* = J_d(q_d)$ is a (inverse) supply curve of the resource d.

If the optimal distribution of production is not satisfactory when taking into consideration the equity criterion or other political criteria, the model could be modified by imposing rules of sharing out non-food crop production among farms. Consequently, the opportunity cost will be higher, as the solution of the modified model shows. Different values of the parameters in the model (for example, the rate of obligatory set-aside or of the quantity of bio-fuel to be produced) gives rise to a new supply curve. Thus, for each non-food crop d, there exists a family of supply curves.

3.4 CASE STUDY AND MODEL VALIDATION

The interval linear programming approach with the minmax regret criterion objective function has been implemented to investigate if the model validity can be improved by this approach. Gross margin intervals have been used in the model for crops that appear in the sample, so that, the number s of interval-valued coefficients can be up to 9. For the initial regret candidates to start the algorithm, we used the LP optimal solutions. The principal effect of the ILP approach with the minmax Regret is: when the difference between the gross margins is relatively small, the minmax regret approach gives more “balanced” solutions, more so when the interval coefficients get larger. In fact, as the intervals get larger, the gross margins for different crops start to overlap or, if they already have an intersection, this increases. It then becomes more difficult for the farmer to anticipate which crop will be more profitable. Hence, the min-max regret approach tends to return more and more balanced solutions as the size of the intervals increase. A detailed discussion on this point is presented by Kazakci and Vanderpooten (2002).

Thus some farmers maximize gross margin while others demonstrate risk averse attitude in the sense of minimising the maximum regret. For each individual farm elementary model a simple algorithm replaces the objective function with that, between gross margin maximization and min-max regret, performing better in terms of proximity of the resulted crop mix to the observed one. This way we end up with a hybrid regional model with a custom objective function for each representative farm. This model has by definition a higher predictive capacity than the initial LP, so it will be used to generate energy crops’ supply curves. For this purpose the procedure proposed in section 3.3 is applied adapted to host minmax regret terms in the aggregate objective function. Then a constraint common to all farms obliges the model to produce fixed quantities of energy crops.

Different factors affect the relative position against classic LP generated supply curves. Not only because the objective function value in terms of total farm gross margin at the minmax regret optimum is lower than the LP optimal value (results in lower opportunity cost), but also that the energy crop giving relatively stable gross margin is appreciated in the farm comparing with other crops with high variability (higher opportunity cost). Depending on the above factors, as well as the interaction with the constraint structure, the minmax supply curves are located to the right of the LP curve up to a certain quantity level. Quantities used in the biofuel industry float in this range, thus we consider that the min-max criterion adoption results in lower opportunity costs of biomass raw material for the biofuel industry. The difference between biofuel estimated cost and its market value indicates the minimal subsidy (equivalent to the excise tax exemption) necessary to make biofuels financially viable. Biofuel costs calculated using minmax regret objective functions are 5% lower than their LP counterparts.

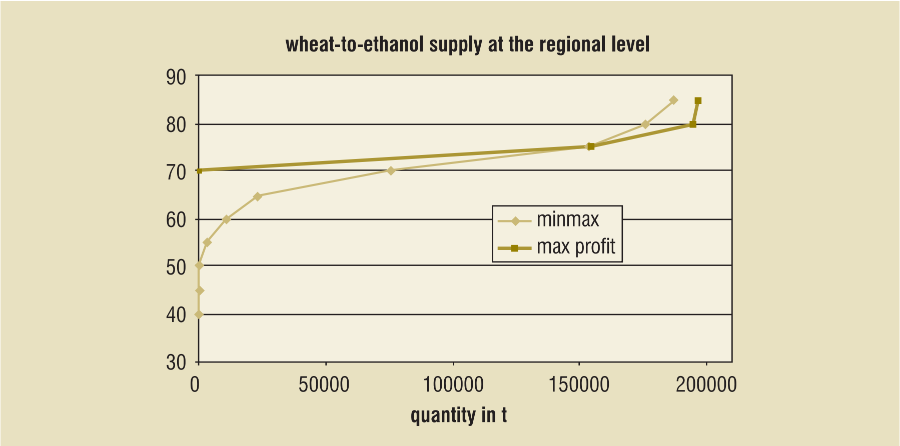

Figure 3.1 Supply curves resulted by max profit and min-max regret objectives at the regional level

3.5 CONCLUSION

This analysis underlines different factors that determine the agricultural raw material cost used for the production of bio-fuels. Certain factors are endogenous to the farms such as crop yields; other factors are exogenous such as agricultural policy decisions, in particular those that relate to the rate of land set-aside. Climatic risks are also a source of cost variation. In addition to cost variation factors that are farm specific, spatial variability exists, which is the result of differences in economic efficiency among farms. The concepts of agricultural supply and opportunity cost resulting from the microeconomic theory, which find an application within the framework of mathematical programming models, allow for modelling of the agricultural complexity with very interesting results.

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