Modelling heterogeneity to estimate the *ex ante* value of biotechnology innovations

Dillen, K. [1], Demont M. [1, 2] and Tollens E. [1]

[1] Centre for Agricultural and Food Economics, Katholieke Universiteit Leuven (K.U.Leuven), Leuven, Belgium
[2] Africa Rice Center (WARDA), Saint-Louis, Senegal

Abstract— **After more than a decade of GM crops, literature reports farmers and consumers can gain significantly from the technology, despite the intellectual property rights assigned to the innovator. In this paper we assess the effect of heterogeneity on this distribution of benefits. A two dimensional framework is created to assess the *ex ante* benefits of an innovation. Given this setting and the scarce data often available, a parametric modelling approach is taken. The two dimensions of heterogeneity, spatial and temporal, are explicitly modelled as they have a different importance for different technologies. Using this framework we can simulate different corporate pricing strategies and evaluate the benefits generated under changing heterogeneity. The framework is tested on the introduction of HT sugar beet in the EU-27.**

Keywords— **Heterogeneity, Parametric modelling, ex ante**

I. INTRODUCTION

Since the commercial introduction of the first generation of genetically modified (GM) crops in agriculture, the value creation and benefit sharing of these technologies have been of great interest to society. Opponents of GM technologies argue that the innovating sector extracts most of the benefits to the expense of farmers and consumers. In contrast to earlier, publicly funded innovations in agriculture, most of the first-generation GM technologies are developed and commercialized by the private sector. The laws and enforcement of IPRs have provided innovating firms with some monopoly power in the market for GM seeds, affecting the value creation and benefit sharing of these technologies [1,2,3,4] The heterogeneous character of farmers[5], results in a downward-sloping aggregate derived demand curve [3] and limited adoption. This suggests that, despite its high value, GM crops are a nondrastic innovation [6], because the monopolist's pricing decision is constrained by the threat of competition [7], leading to 'restricted monopoly pricing' [8] and incomplete adoption [9].

The first generation of GM crops is out there for more than a decade and the first *ex post* impact studies uncover the global value creation and benefit sharing of these technologies. Regardless the variability of the impact estimates a review by Demont *et al.* [10] reveals that, on average, two thirds of the global benefits of first-generation GM technologies are shared among domestic and foreign farmers and consumers, while only one third is extracted by the input suppliers (gene developers and seed suppliers), making abstraction of their cost structure. In this paper we argue that the observed formula of benefit sharing of first-generation GM technologies is a direct reflection of the degree of heterogeneity of crop protection constraints and technology valuations in arable farming and not a strategic choice by the innovator. In *ex post* impact assessments of GM crops, the relevant adoption data are available and implicitly incorporate farmer heterogeneity [11]. *Ex ante* assessments should focus on farmer heterogeneity as the adopting and non-adopting farmer segments are not directly observable to the researcher and homogeneity bias arises [12]. Oehmke and Wolf [13] developed a formal model of pricing to heterogeneous potential adopters and observed a strong negative correlation between monopolistic rents and farmer heterogeneity in the marketing of Bt cotton in the USA. However, their model only includes the spatial dimension of heterogeneity, while it is common knowledge that pest infestations – and hence the value of Bt technologies – are stochastic in the temporal dimension [14]. Therefore we develop a 2-dimensional framework to fully incorporate farmer heterogeneity in *ex ante* impact assessments of innovations.

The paper is organised as follows. In Section 1, we develop a theoretical framework for modelling heterogeneity among potential adopters of a new technology with IPRs. Section 2 derives a demand function for the new technology and assesses the effect of heterogeneity on technology pricing, adoption and benefit sharing. In Section 3, we apply the framework in an *ex ante* assessment of herbicide tolerant (HT) sugar beet adoption in the EU. Section 4 finally concludes.

II. IMPACT ASSESSMENT AND HETEROGENEITY OF TECHNOLOGY VALUATION

We define an innovative technology as a marketable good which allows farmers to surmount an agricultural constraint. Moreover, we introduce the concept of technology valuation to represent the total value of an innovative technology as perceived by potential adopters, including pecuniary as well as non-pecuniary (e.g. see [15]) attributes. It is important to recognize the fact that the innovation does not happen in a vacuum. Certain innovations alter the nature of production decisions from a set of independent decisions over inputs including seed, pesticides and cultivation methods to a smaller set of choices over production systems [16]. The value of an innovative technology should then be calculated as the value of the new production system. Previous research showed that the value of an innovative technology is not uniformly distributed among adopters; some adopters realise a profit from the technology while others rationally choose not to adopt. Therefore GM crops can be distinguished from other yield increasing innovation with a more universal payoff [5]. GM technologies will pay off differentially depending on field conditions, crop rotation, and environmental conditions. Furthermore, the technology valuation to any particular farm will depend on current machinery, managerial expertise, and local market conditions that condition the profitability of GM innovations relative to alternative technologies [5]. Darr and Chern [18] focus on three main factors that condition the adoption decision: farm demographics, farm/field characteristics, and market and environmental factors. In a study of adoption in India, Cameron [19] found similar results and highlighted the role of accumulated knowledge of the performance of the technology. Farm characteristics such as farm size and farm operator demographics (farmer's age, experience, education), and tenure have been found to be statistically significant determinants [20]. These sources of heterogeneity can be classified in two dimensions, i.e. time and space. Temporal heterogeneity arises from the stochastic nature of agricultural constraints, such as pests and diseases. Spatial heterogeneity originates from spatial variability of agricultural constraints, such as agro-climatological characteristics, access to resources and markets, availability of alternative technologies and human capital. Technology valuation in both dimensions is also affected by the attitude towards risk of the potential adopter. Empirical evidence shows that most farmers are risk averse (e.g. [21]). In addition exhibit decreasing absolute risk aversion, meaning them adverse to downside risk [22]. Farmers are averse of being exposed to unexpectedly low returns and this affects their technology valuation and adoption behaviour.

In the *ex post* assessment of value and benefit sharing of an innovative technology, adopters reveal technology valuation through their adoption decisions and technology expenditures. In the literature, *ex post* impact assessments of GM crops through cross-sectional comparisons of adopters' and non-adopters' cropping budgets are widely accepted [11]. In *ex ante* assessment adoption and, hence, self-selection have not even been established and no empirical evidence is available on adopters' revealed behaviour. Most *ex ante* impact assessments draw from cross-sectional comparisons of average cropping budgets [23,24], ignoring heterogeneity of farmers and producing biased results. From an *ex ante* perspective, revealed preference information of an innovative technology is *quasi*-unobservable to the researcher. Stated preference information can be collected through contingent valuation (CV) analysis and an expected demand function for the new technology can be constructed. However, this method requires costly survey data as surveys need to be reproduced in different years and different regions in order to capture both dimensions of heterogeneity. Moreover, farmer preferences are elicited directly based on hypothetical, rather than actual, scenarios. These constraints severely limit the use of CV analysis in large-scale *ex ante* impact assessments.

Therefore, we propose a framework that explicitly models heterogeneity of technology valuation among adopters under scarce data. The conventional direct approach to model heterogeneity among producers is through a probability density function (PDF) [25]. We use this modelling approach for heterogeneous adopters. In the hypothetical case of perfect information, the PDF could be constructed in a non-parametric way. However, in *ex ante* impact assessments imperfect information is endogenous to the problem. Therefore, missing data are replaced by estimations, assumptions and theory. Hence, parametric approaches are usually preferred due to small samples.

If the new technology is a true innovation, technology valuation by farmers, x, is strictly positive, i.e. $x \in [0, \infty[$. Farmers expressing a higher valuation of a new technology are more likely to adopt it. Therefore, potential adopters are more likely to be situated towards the upper tail of the PDF, while non-adopters are more likely to populate the lower tail. However, due to the two-dimensional nature of heterogeneity, x is modelled through a joint PDF of independent variables:

$$f(x) = f_t(t) \times f_s(s) \ , \tag{1}$$

where $f_t(.)$ and $f_s(.)$ respectively represent the temporal and spatial marginal PDFs of x, and $f(.)$ represents the joint PDF of $f_t(.)$ and $f_s(.)$. The cumulative distribution function (CDF) in turn is projected in one dimension in order to derive a normalized demand function $Q(x) \in [0,1]$:

$$F(x) = \int_0^x \int_0^x f(x) \ dt \ dy \quad , \tag{2}$$

$$Q(x) = 1 - F(x) . \tag{3}$$

III. CORPORATE PRICING STRATEGIES IN THE PRESENCE OF HETEROGENEITY

In most *ex ante* impact studies the technology premium (θ) is exogenously introduced in the calculations. Alston *et al.* [26] endogenized θ by looking at first order statistics. The technology price is set at the average technology valuation, known as competitive pricing. Neglecting higher order statistics does not account for heterogeneity and leads to homogeneity bias of the created welfare and a suboptimal profit for the innovators [12]. Homogeneity bias arises as well if only the temporal dimension of heterogeneity is taken into account. Instead of incorporating the variation through time, the observed spatial heterogeneity is taken as the average through time, competitive pricing in time.

However, innovators decide on their price level based on the population of adopters. Throughout the paper we assume that farmers act rational and adopt an innovative technology bundle if $x-\theta \geq 0$, where θ represents the price of the technology bundle. We assume that development costs are sunk and not incorporated in the pricing decision of the innovating firm. Assuming constant marginal costs, *c*, the profit function of a monopolistic innovator is represented by:

$$\pi(\theta) = (\theta - c)Q(\theta) \quad (4)$$

The optimal price of the technology bundle, θ, satisfies the following first order condition:

$$\frac{dQ(\theta)}{d\theta}.(\theta - c) + Q(\theta) = 0\,. \quad (5)$$

Equation 5 implies that the optimal price, set by the innovator, depends on heterogeneity of technology valuation in both the temporal and spatial dimension and their interaction.

Some first comparative statistics of can be calculated using the implicit function theorem and parameterizing the function. Suppose that the distribution is characterized by a mean, μ, and standard deviation, τ, which yields

$$\frac{d\theta}{d\mu} = -\frac{-F_{\mu} + (c-\theta)dF_{\mu}}{-F_{\theta} - dF - dF_{\theta}} \quad (6)$$

where subscript means partial differentiation. In order to determine the sign of the derivative we need extra assumptions. Suppose that dF is unimodal with concave tails and θ lies on the lower tail. Then the denominator is negative and the nominator becomes positive as c approaches 0. In the case profit maximization and the assumption surrounding p, this means that as the average valuation increases, the technology premium will follow.

The effect of a change in variance is determined by

$$\frac{d\theta}{d\sigma} = -\frac{-F_{\sigma} + (c-\theta)dF_{\sigma}}{-F_{\theta} - dF - dF_{\theta}} \quad (7)$$

Under the same assumptions, this derivative will be negative. This means the innovator will drop the price in order to maintain his customer base as the variance or heterogeneity increases. These simple comparative statistics however do not give us enough information. We can not assess the impact of the two dimensions, the impact on profits or the effect of risk attitudes. Due to poor analytical tractability of the models comparative dynamics, numerical simulation is used to examine these effects. In order to examine the effect of the two dimensional heterogeneity on the value creation and the corporate pricing strategy we assume heterogeneity is distributed through a joint Gaussian distribution among farmers with $f_s(s) \sim N(\mu_s, \sigma^2)$ and $f_t(x) \sim N(\mu_t, \tau^2)$. The profit function for the innovating firm changes to

$$\pi(\theta,\mu,\sigma,\tau) = (\theta - C).Q(\theta,\mu,\sigma,\tau)\,. \quad (8)$$

The standard deviation of is an adequate measure of heterogeneity. Without loss of generality we assume $\mu_s = \mu_t = 500$ and we keep spatial heterogeneity constant while varying the value of temporal heterogeneity (because the normal distribution is symmetrical). We assume that the temporal heterogeneity is always smaller than or equals the spatial heterogeneity. The results can be seen in Table 1 and Figure 1.

Table 1 The effect of heterogeneity on technology fee, adoption and value creation

σ	τ	θ	π	Adoption	Benefit farmer	Value
100	20	467.1	458.4	98%	75.1	542.2
100	40	454.1	435.7	96%	93.4	547.5
100	60	448.8	421.9	94%	110.5	559.3
100	80	446.9	413.2	92%	115.2	562.1
100	100	446.4	407.3	91%	124.8	571.2
100	Assumed 0 but in reality 40	391.0	383.6	98%	152.0	543.0

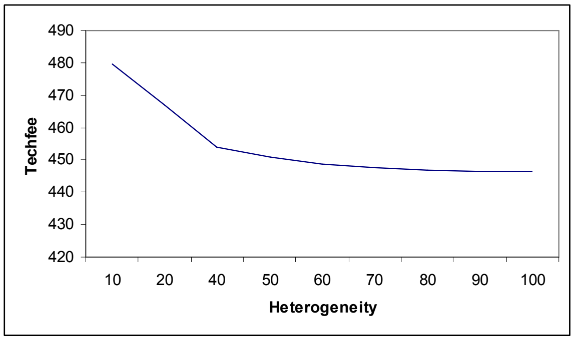

Figure 1 The effect of heterogeneity on the technology fee

Heterogeneity in the temporal dimension has a downward effect on θ. If heterogeneity increases, the density function will become flatter and more scattered. The innovator has to lower his price in order to capture a market share allowing him to maximize his profit. The effect of increasing heterogeneity reduces if the heterogeneity becomes prominent. If the innovator would choose to price the technology competitive in time, we get a θ which is clearly lower than when both dimensions are being taken into account. Using equation 4 and assuming marginal costs are zero we can calculate the profit the innovator makes. Another factor influencing the technology valuation is the risk aversion of the potential adopter. Under risk aversion the technology valuation is affected by a higher variance and increases the effect of heterogeneity. The classic mean variance approach as shown above can be supplemented with a third standard moment, the skewness. Under downside risk aversion, as is the case with farmers (cfr. supra), the technology valuation will be positively skewed [27]. In order to assess this effect a lognormal function would be needed in further research (ongoing).

These results bearing in mind, if IPRs are strong, and the market structure is suitable, third degree price discrimination might be a profitable strategy for the innovator. Since price discrimination in the seed sector has to be spatial, it is the variance of $f_i(t)$ in each submarket which is diminished. For Bt cotton this is the case in the US [28]. Monsanto owning the patents on key genetic events, could require the farmer to sign a technology contract with a "no resale" clause in it, hereby strengthening its monopoly power. The spatial heterogeneity in technology valuation is further diminished by the sensitive reaction of upland cotton varieties to agro-climatic changes [4]. In Europe, price discrimination can be found in Bt maize in spain [29]. These observations show that the innovator is aware that patent-based uniform pricing of a GM-related innovation leaves substantial benefits with the producers, preventing full appropriation by the innovator due to the heterogeneity among farmers [5]. Vertical integration and contracting might provide effective mechanisms for increased appropriation.

The gross value of the crop for farmers in turn can be determined by,

$$\int_0^\infty \int_0^\infty s.t.f(s,t)\,ds\,dt\,. \tag{8}$$

But because of the θ and the rationality of adopters, it is important to determine the marginal adopter [30]. First a one dimensional projection of the density function *f(s,t)* is calculated,

$$f(x) = \frac{d\,F(x)}{dx}\,. \tag{9}$$

The adoption rate ρ can be predicted as

$$\rho = \int_\theta^\infty f(x)dx \text{ or } \rho = 1 - F(\theta)\,. \tag{10}$$

We define $f_a(y)$ as the adopters' density function of technology valuation:

$$f_a(\theta) = \begin{cases} \dfrac{f(\theta)}{\rho} & (x > \theta) \\ 0 & (x \le \theta) \end{cases}\,. \tag{11}$$

The net value of the new technology, $\overline{\alpha}$, for all adopters then amounts to:

$$\overline{\alpha} = \int_\theta^\infty (t-\theta).f_a(\theta)\,d\theta\,. \tag{12}$$

In Table 1 we can see the effect of increasing heterogeneity and risk aversion on the farmer value. The benefits accruing to farmers rise if the heterogeneity among farmers augments. This explained by the reduced technology fee and the increased amount of farmers which can gain a lot from the technology. We can also see that if the innovator chooses to price the innovation competitive in time, the benefits accruing to farmers become much higher (€152/ha versus €93/ha). In the case heterogeneity in both the spatial and temporal dimension is zero, $\overline{\alpha}$ becomes zero and the whole created benefit accrues to the innovator itself in the form of θ and full adoption would be reached. This situation could be reached in cases of contracting or vertical integration.

IV. HETEROGENEITY IN TECHNOLOGY VALUATION IN THE CASE OF HT SUGAR BEET IN EUROPE

A. Selection of a European case study

The case of HT sugar beet is very appealing for EU agriculture as this crop is grown in most EU countries. We understood that the major impediment comes from the concentrated group of refiners, processors and manufacturers of sugar and sugar-containing products. Processors face risks related to market acceptability of sugar and by-products [31]. However recently, it seems the sugar processors have opened their doors to biotechnology following the food and feed approval in Australia, New Zeeland, Japan and the EU. HT sugar beets are commercially introduced glyphosate in the USA in 2008. These events combined with the increasing importance of sugar beets as a raw material for biofuels makes the introduction of HT sugar beets becomes reasonable for the EU in the future.

B. Modelling heterogeneity among sugar beet farmers in the EU

For economic sugar beet production, effective weed control is crucial. Yield losses can be up to 100%, such is the poor ability of beet to compete with the large range of weeds present in arable soils [32]. Because of the economic importance, the cost of herbicide use is the determining factor in the technology valuation of HT sugar beet. In contrast to pests and diseases, the infestation level of weeds is constant over time, which means the temporal dimension of heterogeneity is zero. A one-dimensional representation of heterogeneity seems to be sufficient for HT sugar beet. In the case of Bt crops, the temporal dimension plays a important role because insect populations vary through time which makes a two-dimensional approach necessary. Herbicide and application costs for the EU countries are reported by Hermann [33,34,35]. These values indicate some heterogeneity, but in order to construct the expected demand curve we need the PDF. Survey results from the Netherlands [36] and France have been analysed [37,38] and the CDF best fitting on these data is the loglogistic CDF, see Table 2 (followed by the Beta and Gamma function),

$$CDF(x) = \frac{1}{\left[1 + \frac{x}{\gamma.}\right]^{-\delta}} \tag{12}$$

with γ en δ scale and shape parameter respectively (see Table 3).

Table 2 Fitted CDF around survey data of herbicide expenditures in sugar beet

	Model: x=1/(1+(Herbicide exp/ γ)**(- δ)) Dep. var: x Loss: (OBS-PRED)**2					
	France,1997		France,2000		Netherlands,2004	
	γ	δ	γ	δ	γ	δ
Estimate	103.3	4.8	160.2	4.7	803.3	5.0
Std.Err.	1.0	0.2	0.4	0.04	3.7	0.1
t	94.1	22.1	440.4	101.5	214.2	47.1
p-level	3.3E-22	7.5E-13	0	0	0	0
R	0.99852		0.99981		0.99917	

Table 3 Herbicide PDF based on herbicide product and application costs in the EU-27 (real 2007 currency)

Member State	Min (€/ha)	Mean (€/ha)	Max (€/ha)	Distribution herbicide costs	nc	ng	g (l/ha)	k (€/ha)	pgl [d] (€/l)
Austria	156	311	467	Loglogistic(0; 260.8; 5.4323)	2.5	2.5	6	41.5	4.37
Belgium	104	261	417	Loglogistic(0; 206.59; 4.2293)	3.5	2.5	6	18.5	4.37
Germany	76	206	334	Loglogistic(0; 160.33; 3.9367)	3	2.5	6	18.2	4.37
Spain	141	261	381	Loglogistic(0; 222.94; 6.0868)	3	1	3	13.0	4.37
Czech Republic	138	198	276	Loglogistic(0; 180.12; 9.9884)	3[c]	2.5[c]	6	2.5	4.37
France	103	150	206	Loglogistic(0; 135.78; 9.7149)	3.8	2.5	6	20.0	4.37
Finland	154	220	297	Loglogistic(0; 200.67; 10.044)	3.8	2.5	6	16.4	4.37
Greece	94	132	202	Loglogistic(0; 121.06; 10.519)	1.5	1	3	17.5	4.37
Italy	95	169	253	Loglogistic(0; 145.32; 6.3659)	2.5	2.5	6	15.3	4.37
Ireland	64	93	122	Loglogistic(0; 84.422; 9.68)	3	2.5	6	13.3	4.37
Netherlands	135	176	238	Loglogistic(0; 164.32; 13.483)	3.5	2.5	6	40.4	4.37
Poland	121	214	332	Loglogistic(0; 184.91; 6.3962)	3[c]	2.5[c]	6	7.3	4.37
Sweden	77	186	308	Loglogistic(0; 148.56; 4.2881)	2.9	2.5	6	13.3	4.37
UK[e]	78	149	225.	Loglogistic(0; 124.05; 5.9299)	4.6	2.5	6	14.4	4.37
Denmark[e]	88	212	372	Loglogistic(0; 165.51; 4.3522)	4	2.5	6	26.0	4.37
Portugal[a]	141	261	381	Loglogistic(0; 222.94; 6.0868)	3	1	3	13.9	4.37
Hungary[b]	64	159	211	Loglogistic(0;132.28;2.7296)	3.3[c]	2.5[c]	6	2.5	4.37

Sources: Hermann [33,34,35] and Schaüfele [45]
[a] Portugal identical to Spain
[b] No data from Hermann, data from [46]
[c] No data from Schaüfele, data from Germany
[d] We use one constant price throughout the EU in order to keep the analysis transparent.
[d] No data from 2004

Comparing the expert values with the fitted distribution delivers percentiles for each of the three expert values. We assume these percentiles remain constant for the different EU member states. It seems reasonable the concept of minimum, average and maximum remained the same for Hermann throughout the Member States. This allows us to construct a loglogistic PDF for the technology valuation for each Member State of the EU-27 in 2004 (Table 3 in real 2007 currency). The omitted Member States only produce 4% of the EU production. The distribution in technology valuation in each member state,

$$f(x)=\frac{\delta.\left[\dfrac{x}{\gamma.(1-red)}\right]^{\delta-1}}{\gamma.\left[1+\left[\dfrac{x}{\gamma.(1-red)}\right]^{\delta}\right]^{2}} \tag{13}$$

and $$F(x)=\frac{1}{\left[1+\dfrac{x}{\gamma.(1-red)}\right]^{-\delta}} \tag{14}$$

with x herbicide expenditure, γ and δ the scale and shape parameter respectively and *red* the reduction of prices in the conventional herbicide market. Since herbicides are protected with IPR, producers also possesses some kind of market power which allows them to sell at price levels above the marginal cost. When a new competing technology enters the market, the producers of conventional herbicides will react with a price reduction. This reaction has taken place with the introduction of HT soybeans in the US and can be seen with the introduction of generic products on the herbicide market [39]. A price reduction of 20% on the competing the conventional herbicide in Europe following introduction of the HT technology is assumed.

C. Corporate pricing strategy

Before a price decision about the optimal θ can be made by the innovator, the demand function is needed. Using equation 3 and 4 we can construct the normalized demand function for each member state,

$$Q(\theta) = 1 - Cd(\theta) \tag{15}$$

with $$\theta = x + (nc - ng).k - pgl.g \tag{16}$$

representing the price difference in total application cost between the old and the new bundle and with *nc* and *ng* the number of applications for conventional and glyphosate respectively, *k* the cost of one application, *pgl* the price for a litre glyphosate and *g* the dosage of glyphosate (Table 3). This way of calculating the technology valuation follows from the production system approach (cfr.supra). From which the profit function becomes:

$$\pi(\theta) = Q(\theta).(\theta).n \tag{17}$$

if we assume marginal costs are zero and n the total area planted with sugar beet from F.O.Licht [40], the technology fee, θ, can be retrieved using equation 5.

Although the data is available to the innovator to price discriminate (results in Table 4), the situation in the sugar industry does not favour this pricing strategy. The sugar sector is highly concentrated and vertically coordinated. The sugar producer buys the seed from the seed company and supplies them to the farmers in a highly coordinated contract. Due to these contracts, the amount of seed buyers on the market, which often operate in multiple countries, is small and price discrimination among countries is unrealistic. A uniform pricing strategy seems the more realistic option given these constraints. This assumption is confirmed by the uniform pricing strategy upon introduction of HT sugar beet in the VS [41]. A demand function is constructed based on the production-weighted average of the countries responsible for 75% of the European production. The cumulative distribution

$$F(x) = \sum_{i}^{n} Cd_n(x).share_n \tag{18}$$

with n the number of countries taken into account and $share_n$ the share in production over the n countries. Applying equation 12-17 while replacing the parameters by their weighted average gives us the uniform technology fee of €88/ha for 2004 (Table 5). The calculated technology fee seems rather high compared with other crops. However they are in line with the prices for the introduction from HT sugar beet in the VS, €90-106/ha [41]. This can be explained by the high economic importance of herbicides in the growing stage of sugar beet compared to the other crops assessed.

D. Value of the innovation to farmers, innovator and the total value

A common measure of the value of a GM crop is the value per ha. In order to calculate the value per ha, or the rents, accruing to farmers, we use the land function as introduced by Lapan and Moschini [42] in the case of HT soybeans. The land function is calibrated on real observed data [43] and uses,

$$\overline{\alpha}_i = \int_{\lim_{i,j}}^{\infty} f_a(x,i).(x - \lim_i)dx$$

with $$\lim_i = pgl.g_i + \theta_i + (ng_i - nc_i).k_i \tag{19}$$

$$\rho_i = 1 - F(\lim_i, i) \tag{20}$$

$$f_a(x,i) = \begin{cases} \dfrac{f(x,i)}{\rho_i} & (x > \lim_i) \\ 0 & (x \le \lim_i) \end{cases} \tag{21}$$

and i (1…17) the Member States.

The results can be seen in Table 4 and Table 5.

Table 4 Technology fee, farmer rent and innovators profit under price discrimination

Member State	Technology fee (€/ha)	Farmer rent (€/ha)	Revenue innovator (million €)	Value of the crop (€/ha)
Belgium	123	131	8.1	254
Denmark	106	122	4.3	228
Germany	94	99	26.5	193
Greece	75	95	2.2	170
Spain	145	135	12.9	280
France	87	133	27.0	220
Ireland	50	32	0.7	82
Italy	77	59	9.7	136
The Netherlands	121	118	11.2	239
Austria	147	123	4.9	270
Portugal	170	145	1.2	315
Finland	125	68	3.5	193
Sweden	86	74	2.5	160
United Kingdom	78	117	8.8	195
Czech Republic	98	87	5.6	185
Hungary	108	63	2.6	171
Poland	102	79	22.4	181
EU-27		average 99	154.0	average 204

Table 5 Technology fee, farmer rent and innovators profit under uniform pricing

Member State	Technology fee (€/ha)	Rent farmer (€/ha)	Revenue innovator (million €)	Value of the crop (€/ha)
Belgium	88	174	7.2	262
Denmark	88	145	4.0	233
Germany	88	108	26.3	196
Greece	88	63	1.8	151
Spain	88	192	9.0	280
France	88	131	26.9	219
Ireland	88	1	0.003	89
Italy	88	45	8.6	133
The Netherlands	88	151	8.6	239
Austria	88	188	3.8	276
Portugal	88	223	0.7	311
Finland	88	102	2.7	190
Sweden	88	71	2.5	159
United Kingdom	88	99	8.5	187
Czech Republic	88	101	5.6	189
Hungary	88	78	2.4	166
Poland	88	96	22.0	184
EU 27		average116	141.0	average 204

Third degree price discrimination allows the innovator to make a profit at least as high as uniform pricing as predicted by the framework. The farmer rent under price discrimination is lower than under uniform pricing as expected. The bigger heterogeneity in the case of uniform pricing makes more benefits accruing to farmers. The total value per ha is composed by the technology fee and the rents and remains the same under both corporate pricing strategies. However, the reaction of the total value per ha with increasing heterogeneity depends on the distribution of technology valuation. The increase in farmer benefit can be offset by the decrease in technology fee. It is clear from the results that the sharing-out between upstream and downstream will be affected by the amount of heterogeneity. However, Frisvold [44] argues that the sharing-out can not be addressed adequately without aggregating the results and integrating market effects. The aggregation of benefits upon introduction of HT sugar beet in the world can be found in [43] which in detail describes the aggregation and the policies affecting the sharing-out.

V. CONCLUSIONS

Heterogeneity among potential adopters of a new technology is an important determinant in the outcome of impact assessments of new technologies. In *ex post* impact studies, the heterogeneity is endogenous to the real adoption data. In *ex ante* impact assessment however, the heterogeneity has to be modelled explicitly. Heterogeneity arises from two sources, temporal and spatial. The results of our three-dimensional framework show both of them affect the expected demand curve for a new technology. Based on this expected demand curve, the private innovator will set his price in order to capture monopoly rents based on IPRs. Increasing heterogeneity makes an optimal pricing of the technology difficult and decreases both the technology fee and the profit for the innovator. On the other hand, the more farmers vary in their valuation of a new technology, the bigger the rents accruing to them. The typical heterogeneity among farmers explains the rule of thumb in sharing-out, 1/3 upstream and 2/3 downstream. In the extreme case heterogeneity would be absent, the whole value of a crop would accrue to the innovator in the form of a perfect priced technology fee. These results can have important consequences for future innovations in agriculture. Most innovations have the tendency to decrease the difference in technology valuation among farmers. For instance, farmers adopting HT crops will replace several different conventional herbicides by one systemic, broad-spectrum herbicide. The easiness of management increases and differences in application rates reduces. Another strategy for the farmer could be to reduce the risk through selling insurance and as such reduce the variance in technology variation. All of this makes the technology valuation much more homogeneous among farmers. The decreased heterogeneity among farmers allows the innovator of a future innovation, protected by IPR's, to introduce its next innovation at a better targeted, profit optimizing technology fee. This would leave less of the generated benefits left for the farmers.

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The address of the corresponding author:

- Author: Koen Dillen
- Institute: Centre for agricultural and food economics, KULeuven
- Street: de Croylaan 42 bus 2424
- City: 3001 Heverlee
- Country:Belgium
- E-mail: koen.dillen@ees.kuleuven.be

Email