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Predicted Willingness of Irish Farmers to Adopt GM Technology

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In this article, we use a probit model to assess the factors that will influence the decision of Irish farmers to adopt genetically modified (GM) technology should they be given a choice in the near future of selecting between GM and non-GM varieties of crops. The results from the probit model indicate that among the likely early adopters of GM technology in Ireland are farmers with large farm acreage who are specialist crop farmers and who have formal agricultural education together with access to high-quality soils. Contrary to expectations and theory, the farmer's age was insignificant in the final specification of the model. Neither tenure nor profitability had any influence in determining the likelihood of adoption once farm size was accounted for, indicating that farm size may dominate other farm-level characteristics.

Key words: adoption and diffusion theory, GM technology, Ireland, probit models, technological innovations.

Introduction

At present, there is no cultivation of GM crops in Ireland. There are a number of reasons for this. First, none of the GM lines currently authorized for cultivation across the member states of the European Union (EU) are suited to the Irish agri-environment, and political concerns about the cultivation of GM crops also exist. As such, it is difficult to assess what factors will influence the decision of Irish tillage[1] farmers to adopt GM crops should they be given the choice in the near future of selecting between GM and non-GM varieties.

The use of new agricultural technologies has generally been found to be a function of farm and farmer characteristics and specific features of the particular technology (Feder, Just, & Zilberman, 1985; Marra & Carlson, 1987; Rahm & Huffman, 1984). A considerable set of literature has developed regarding factors that influence the adoption of new technologies by farmers through use of innovativeness theory (Feder et al., 1985; Griliches, 1957; Rogers, 1995). Adoption and diffusion theory has been widely used to identify the factors that influence an individual's decision to adopt or reject an innovation. Rogers (1995, pp.11) defined an innovation as "…an idea, practice or object that is perceived as new by an individual or other unit of adoption. The perceived newness of the idea for the individual determines his or her reaction to it." He further identified five characteristics of an innovation that affect an individual's adoption decision.

1. Relative advantage: how the innovation is better than existing technology
2. Compatibility: the degree to which an innovation is seen as consistent with existing experiences, needs, and beliefs of adopters
3. Complexity: how difficult the innovation is to understand and use
4. Trialability: the degree to which the innovation may be used on a limited basis
5. Observability: the degree to which the results of an innovation are visible to others

The relative advantage and observability of an innovation represent the immediate and long-term economic benefits from using it, whereas compatibility, complexity, and trialability indicate the ease with which a potential adopter can learn about and use an innovation (Boz & Akbay, 2005; King & Rollins, 1995). As the relative advantage, compatibility, complexity, trialability, and observability of GM crops has caused more farmers to grow them worldwide each year, we can study the adoption of these crops as an innovation.[2]

Several ex-ante impact assessments on the cultivation of GM crops in Europe have been based on compar-

1. *Tillage farmers are defined in the Irish National Farm Survey as farmers that are principally involved in the production of cereals, oilseeds, and protein crops, in addition to farms involved in other field cropping.*

2. *As of 2007 the global GM crop area measured 114.3 million hectares, a 12% increase when compared to 2006, and the number of countries planting GM crops increased to 23 (James, 2007).*

ative analysis of first-order statistics (e.g., means) of cross-sectional datasets (Flannery, Thorne, Kelly, & Mullins, 2004; May, 2003). This approach ignores farmer heterogeneity and fails to separate potential adopters from non-adopters (Demont et al., 2008). The role of heterogeneity across agents has been recognized in the adoption literature (Feder et al., 1985; Sunding & Zilberman, 2001). To ensure our analysis is heterogeneity inclusive, specific farm and farmer characteristics were analyzed in a probit econometric model to determine the characteristics of early adopters of GM technology.

The next section describes the farm and farmer characteristics that should be incorporated into the analysis. Next, we outline the econometric model, followed by the section discussing the dataset used in the analysis and the variables derived. The final two sections present results and conclusions.

Background

A basic hypothesis regarding technology transfer is that the adoption of an innovation will tend to take place earlier on larger farms than on smaller farms. It has been hypothesized that larger farmers would be more receptive to innovation than their smaller neighbors and that this was largely due to cost issues. Just, Zilberman, and Rausser (1980) and Feder and O'Mara (1981) demonstrated that given the uncertainty and the fixed transaction costs associated with adopting innovations, there may exist a critical lower limit on farm size that prevents smaller farms from adopting. As these costs increase, the critical size also increases. Thus, innovations with large fixed transaction and/or information costs are less likely to be adopted by smaller farmers (Fernandez-Cornejo & McBride, 2002; Fernandez-Cornejo et al., 2007). Breustedt, Muller-Scheesel, and Latacz-Lohmann (2008), in a German study forecasting the adoption of GM oilseed rape, found that farm size had a positive effect on adoption. Marra, Hubbell, and Carlson (2001) found that farm size had a positive influence on the adoption of Bt cotton in the Southeast United States. Fernandez-Cornejo, Klotz-Ingram, and Jans (2002), in a US study of the adoption of herbicide-tolerant (HT) soybeans, found that adoption rates increased with the size of the farm operation.

Land ownership is widely believed to encourage the adoption of new technologies (Daberkow & McBride, 2003). Fernandez-Cornejo et al. (2002; 2007) hypothesized that tenants can be assumed less likely than landowners to adopt new technological innovations, as the benefits may not necessarily flow to them, while land ownership is likely to influence the adoption decision. However, there has been some disagreement in the literature regarding this hypothesis (Feder et al., 1985). It has been suggested that the inconsistencies in the literature are likely due to the nature of the technological innovation being examined. Regardless of these disagreements, the effect of tenure on the adoption of new technologies should be examined.

In addition to land ownership and farm size, profitability is likely to be another significant farm-level factor influencing the decision to adopt. Farmers with access to large financial resources have the ability to adopt innovations earlier. Should a considerable investment be required, this can be expected to favor the more profitable farmers, as investments in innovations often require fixed expenditures and are more risky than investments in more mature technologies. Both Hoff, Braverman, and Stiglitz (1993) and El-Osta and Morehart (1999) found that credit constraints may hamper adoption behavior. For example, Boz and Akbay (2005), in a study examining the adoption of maize in a Turkish province, found that early adopters had high levels of profitability. In a Dutch study, Diederen, Van Meijl, Wolters, and Bijak (2003) found that farmers with high solvency ratios were less likely than others to be early adopters of technological innovations. It is possible that farmers may have high solvency ratios due to risk aversion and reluctance to invest in innovations. This issue will be examined in the subsequent analysis.

In agriculture, technological innovations typically have been perceived as riskier than traditional agricultural practices (Feder et al., 1985; Griliches, 1957; Sunding & Zilberman, 2001). Innovators and early adopters of new technology are considered more likely to take risks than the majority of other farmers.

The human capital of the farmer is also assumed to have a significant bearing on the decision to adopt new technologies. Most adoption studies have attempted to measure human capital through the farmer's age and their education or years of experience growing the crop (Fernandez-Cornejo, Daberkow, & Huang, 1994; Fernandez-Cornejo et al., 2007). Education of the farmer has been found to have a positive effect on adoption of GM oilseed rape in Germany (Breustedt et al., 2008) and on Bt and HT corn adoption in the United States (Fernandez-Cornejo & McBride, 2002; Marra et al., 2001). It is assumed here that more years of education will increase the probability of adoption, as better educated farmers (farmers with some third-level qualification) can be expected to be more aware of the positive benefits associated with new GM technologies. In addition, if the farm operator has formal agricultural education it is assumed that he/she will be more likely to innovate due to the higher associated skill level. The agricultural system in which the farmer primarily specializes is likely to also influence the farmer's agricultural experience and human capital. The particular soil type on the farm may also influence the adoption decision and account for any potential regional differences.

It is assumed that the younger the farmer, the more likely he/she is to adopt innovations early in his/her respective life cycle (Rogers, 1995). Older farmers may have a shorter time horizon and be less likely to invest in novel technologies. Alexander and Van Mellor (2005) found that GM corn adoption increased with age for younger farmers as they gain experience and increase their stock of human capital but declines with age for those farmers closer to retirement. Experience is measured by whether the farm operator is a specialist crop farmer. These farmers can be assumed to have greater knowledge and awareness of tillage crops, including GM crops, than farmers in other agricultural sectors. A number of studies did not find strong evidence to support the hypothesis that age of the farm operator has an impact on the adoption decision (Boz & Akbay, 2005; Daberkow & McBride, 2003), which contradicts the innovations theory.

If GM crops provide Irish farm operators with greater flexibility in crop management, farm operators have the opportunity to work more hours off the farm to gain additional income. Fernandez-Cornejo, Hendricks, and Mishra, (2005), in a US study, found that the adoption of HT soybeans significantly increased off-farm household income for US soybean farmers and, accordingly, total household income. The authors argued that farmers were induced to adopt HT soybeans due to the simplicity and flexibility of the weed-management control program, which freed up management time. As the number of farm operators in Ireland engaged in off-farm work has increased in recent years, we decided to incorporate this characteristic into the analysis. The 2007 National Farm Survey showed that on 58% of all farms, either the farmer and/or the spouse had an off-farm job (as reported by Teagasc, 2008). This compares with a figure of 52% in the 2004 National Farm Survey and is indicative of the upward trend in recent times.

In a German study forecasting the adoption of GM oilseed rape, Breustedt et al. (2008) incorporated several family characteristics into the analysis. These included the gender of the farmer, whether there were children under the age of 16 present on the farm, and whether there was a successor present. Female farmers and the presence of children had a significant and negative effect on the adoption decision. The significance of these family characteristics in the adoption decision will also be examined.

Methods

Conventional regression analysis (Ordinary Least Squares or OLS) cannot accommodate zero observations on the dependent variable, and the failure of OLS to deal properly with such data led to the development of estimators built on the principle of maximum likelihood (MLE). Limited Dependent Variable (LDV) models are estimated using MLE; the most common of these that are used in adoption literature are the logit model (which corresponds to a logarithmic distribution function) and the probit model (which assumes an underlying normal distribution). Anemiya (1985) concluded that the choice of which continuous probability distribution to use cannot be justified on theoretical grounds. Following Vanslembrouck, van Huylenbroeck, and Verbeke (2002), we chose the probit model. The probit model, or variants of (such as the biprobit), have been used in a number of studies of adoption behavior (Alexander & Van Mellor, 2005; Boz & Akbay, 2005; Breustedt et al., 2008; Fernandez-Cornejo et al., 2002).

In this study, farm and farmer determinants for the adoption of GM technology among Irish farmers are identified and estimated. This research question was tested empirically by the following model.

$$P\{y_i = 1 | x_i\} = F(x_i, \beta) \quad (1)$$

This binary choice probit model describes the probability that y_i=1 for the given function F(.); the vector $\mathbf{x}_i$ containing individual and farm-level characteristics; and where F is also a function of the cumulative distribution function, which is bound by the [0,1] interval i.e., $0 \leq F(x_i, \beta) \leq 1$. Beta is the parameter in the model to be estimated. This implies that the probability that a farmer has considered or investigated growing GM crops depends on specific characteristics, such as farm size, tenure, profitability, and demographic characteristics.

As this model is estimated using MLE, it cannot be interpreted in the same manner as an OLS regression, and, as a result, it is necessary to compute marginal effects to properly interpret the results of the model. The goodness-of-fit was examined using the pseudo R^2 and

McFadden R^2 values. Common to studies using cross-sectional data (which contain a high proportion of zero observations on the dependent variable), these values are not expected to be very high, unlike R^2 values in an OLS regression, for example. Likelihood ratio tests were used to determine which variables should be incorporated into the final specification of the model.

Data and Variables

The data used in this study were taken from the Teagasc National Farm Survey (NFS) for 2006 (Teagasc, 2007). The primary purpose of this study is to collect and analyze information relating to farming activities in Ireland, including accounting, performance, and demographic characteristics. A farm accounting book is recorded on a random representative sample of farms throughout the country. In the 2006 survey, 1,159 farmers were surveyed representing 113,068 farmers. In addition to the main survey, additional special studies on specific topics are conducted throughout the year. The 2007 summer 'special study survey' was concerned with, among other things, a farmer's attitudes towards the adoption of GM technology. Though this survey was conducted by the NFS, not all of the respondents from the 2006 main survey participated in the 2007 special survey. Hence, to link the two datasets, it was necessary to construct a matched-balanced dataset. All observations that appeared in both the 2006 main survey and the 2007 special survey were retained in the final sample, with all other observations purged. As a result, the final sample was smaller than that of the original 2006 NFS sample. The final sample used in this article is 841 farmers, which represents a population of 82,091 farmers, using a weighting system representing size and system of production.

Two of the questions asked to farmers about their intentions toward GM crops were used to create the dependent variable used in this article.

- Would you use genetically engineered crops or seeds (GMOs) if they afforded cost savings over conventional crops/seeds?
- Would you use GMO crops or seeds if they provided greater flexibility in crop-management practices?

Using these two questions, one dependent binary variable was created (*gmtech*), which takes the value of 1 if the farmer is willing to grow a GM crop if it provides either cost savings or greater flexibility in crop management and 0 if otherwise. Definitions and descriptive statistics of all the variables used in the analysis are shown in Table 1. Results for the dependent variable show that 26% of the farm operators surveyed indicated that they would consider growing GM crops should they provide cost savings or greater flexibility in crop management.

Farm size (*Size*) is a continuous variable with the size of farm in hectares (ha). This variable represents the utilized agricultural area (UAA) of the firm. Size squared is also included in the model to assess whether there is a threshold or life-cycle effect on the farm whereby the likelihood of adoption diminishes at some point. In this analysis, it is hypothesized that larger farmers will be more likely to adopt GM crops. Statistics in Table 1 show that the average farm size is 35.51 ha, and there appears to be a wide range—with the minimum at 5.86 ha and the maximum at 377.20 ha.

Two variables representing the share of land owned (*Land*) and the share of land rented (*Rent*) are incorporated into the model. *Land* is a continuous variable and expresses the amount of land owned by the farmer as a percentage of the farmer's UAA; as indicated in Table 1, *Land* represents the majority of UAA on the average farm, at 90%. The *Rent* variable is a dummy variable which takes the value of 1 if the respondent rents additional acreage and 0 if otherwise. The summary statistics in Table 1 indicate that 40% of the farms in the sample rent additional acreage.

The profit variable (*Profit*) represents historic profitability, *not* expected future earnings from adoption of the new technology. Family farm income in 2006 is used as a proxy for the profitability of Irish farms. As new technologies may require additional investment, profitability is expected to significantly influence adoption of GM technology. Table 1 shows that average profitability on Irish farms in 2006 was just over €16,500, but the diverse nature of Irish farms is highlighted with several farms having made substantial losses in 2006.

In this analysis, the human capital of the farmer will be measured through analysis of various demographic characteristics, such as the age (*Age*) and education level (*Educ*) of the farm operator. In this sample, the farmer's average age is approximately 55 years. The education variable is continuous and ranges from 1 to 6, with values of 4 and over representing more highly educated farm operators.[3,4]

The formal agricultural education (*Ageduc)* attained by the farm operator is also represented in the model. Farmers with formal agricultural education are assumed to have greater agricultural awareness than other farmers, and this variable is assumed to positively influence

Table 1. Summary statistics of the variables used in the analysis. (n=841)

Variable	Description	Mean	Standard deviation	Minimum	Maximum
	Dependent variable				
Gmtech	In favor of GM technology if it provides cost savings or greater flexibility in crop management	0.26	0.44	0	1
	Independent variables				
Size	Size of farm in hectares	35.31	31.03	5.86	377.20
Land	Share of land owned	0.90	0.19	0	1
Rent	The farmer rents land from other farmers	0.40	0.49	0	1
Profit	Family farm income in 2006 (€'000)	16.81	21.62	-16.67	235.88
Age	Age of farmer	55.23	12.73	20	83
Educ	Education level of the farmer (scale 1-6)	1.98	1.02	1	6
Aged	Farmer has formal agricultural education	0.44	0.50	0	1
Ofarm	Farmer has an off-farm job	0.38	0.48	0	1
Risk	Farmer's attitudes to new technology such as energy crops	0.05	0.21	0	1
Soil1	Farmer's soil has a wide use range	0.49	0.50	0	1
Soil2	Farmer's soil has a mixed use range	0.40	0.49	0	1
Dspec	Respondent is a specialist dairy farmer.	0.16	0.37	0	1
Doth	Respondent is engaged in dairy & other production.	0.08	0.28	0	1
Crear	Respondent is predominantly engaged in cattle rearing.	0.28	0.45	0	1
Coth	Respondent is engaged in cattle & other production.	0.24	0.43	0	1
Sheep	Respondent is predominantly engaged in sheep production.	0.17	0.37	0	1
Female	Female farmer	0.04	0.20	0	1
Children	School-going children present on the farm	0.32	0.47	0	1
Successor	One child has formal agricultural education	0.03	0.18	0	1

the adoption of GM technology. Table 1 shows that 44% of farm operators in the sample have formal agricultural education.

In this sample, 38% of farmers have an off-farm job. Having an off-farm job is assumed to increase the likelihood of a farmer adopting GM crops, as HT crops provide greater flexibility in crop management and opportunities to earn additional income. In a preliminary stepwise regression procedure this (*Ofarm*) variable had no significant relationship with the adoption decision and also exhibited a negative sign, which is contrary to expectations.[5] However, the variable had a relationship with other explanatory variables and it was decided to include it in the model.

As discussed in the background section, it is important to include a measure of farmers' risk preferences into the model. In this study we assume that if a farm

3. *A dummy variable was also created for higher-educated farmers with the variable taking the value of 1 if the farmers' education was 4 or higher and 0 if otherwise. This returned no significance in the stepwise regressions, so it was decided to proceed with the education variable.*
4. *While selecting and testing the independent variables used in the final specification of the model, the squared term of profit and age were both considered. However, neither variable was significant in stepwise regressions or in the final model specification.*
5. *A further variation of the off-farm work variable (which examined the number of standard man units used to operate the farm) was considered for inclusion in the model. Based on definitions from the National Farm Survey a farm which requires less than 0.75 standard man units to operate is defined as a part-time farm. However, consistent with the findings of the off-farm work variable, the part-time work variable was also found not to have a significant effect on the farmer's willingness to adopt GM technologies.*

operator expressed a positive attitude towards growing energy crops then they are more willing to be innovators and invest in new technologies than other farmers. *Risk* assesses the farm operator's attitudes towards energy crops—such as willow and miscanthus—and takes the value of 1 if the farmer expressed willingness to grow these crops and 0 if otherwise. These crops are relatively new to Ireland and many energy crops require considerable investment before a profit can be accrued, so they can be viewed as a risky venture. Table 1 shows that 5% of respondents in the sample expressed a willingness to consider growing energy crops. The variable had a positive but insignificant effect on the adoption decision in a stepwise regression. However, it was decided to incorporate the variable into the model given the need to capture the effect of farmers' risk preferences.[6]

Soil quality is included in the model as a measure of regional location. The National Farm Survey assembles soil quality into three categories: wide-use range, mixed-use range, and limited-use range, i.e., peripheral or marginal land. In this analysis, it is hypothesized that farmers with *Soil1* (wide-use range) and S*oil2* (mixed-use range) will be more likely to adopt GM technology than farmers with soils of a limited-use range (who form the base category, *Soil3*). Forty-nine percent of respondents have access to *Soil1*, while 40% of respondents have access to *Soil2*.

The National Farm Survey dataset also provides data on the farm system under which each respondent is classified. There are six categories in the dataset: specialist dairy farmers, dairy and other farmers, cattle-rearing farmers, cattle and other farmers, mainly sheep farmers, and specialist tillage farmers. We decided to incorporate dummy variables for each farm system into the model to assess what effect being engaged in a specific type of farming would have on the decision to adopt GM crops. It was furthermore assumed that specialist tillage farmers would be more likely to adopt than other farmers, given their likely superior knowledge of crop-production systems. Therefore, the base category is comprised of specialist tillage farmers—7% of the sample. Five dummy variables were generated for each of the other individual farm systems, e.g., specialist dairy farmer (*Dspec*), dairy and other farmer (*Doth*), cattle-rearing farmer (*Crear*), cattle and other farmer (*Coth*), and sheep farmers (*Sheep*).

An examination of specific family-characteristic variables indicates that just 4% of farmers are female. In addition, 32% of farmers had school-going children present on the farm, and 3% of farms in the sample had an identified successor. However, none of these variables were significant in their respective stepwise regressions nor were they statistically significantly correlated with the dependent variable.[7]

Results and Discussion

The results of the probit model on the likelihood of a farmer adopting GM technology are presented in Table 2, with marginal effects shown in Table 3. Both were estimated using STATA. The model is statistically significant at the 1% significance level based on a likelihood ratio test. In the case of the continuous explanatory variables, the marginal effect relates to a one-unit change in the variable. For the binary explanatory variables, the marginal effect is the difference in probabilities between setting the explanatory variable to 1 and setting it to 0, given that all other explanatory variables are set at their sample means.

We will first examine the results for the farm-level characteristics. The size of the farm has a positive and significant effect on adoption behavior of farmers, suggesting that larger farmers are more likely to adopt new technologies should they result in some benefit accruing to themselves. However, the results for the squared term are insignificant, indicating that there appears to be no threshold effect. The marginal effects illustrate that a one-unit increase in farm size increases the probability of GM technology adoption by 0.0025.

Both tenure variables had an insignificant effect on technology adoption in the model, though they were both significant in their respective stepwise regressions. While the *Land* variable had a negative effect on technology adoption in a stepwise regression, and *Rent* had a positive effect, both variables have a negative sign in the final model, once other factors are controlled. This result suggests that once farm size is controlled for, the

6. *A debt/asset ratio was also constructed, but this variable was found to be insignificant in both stepwise regressions and in the full model specification. Accordingly, the analysis proceeded with farmers' attitudes towards energy crops used as the proxy for risk preferences.*

7. *All three family-characteristics variables were excluded from the final specification of the model. They returned no significance in their respective stepwise regressions nor in the full model, which included other farm-level and farmer-specific characteristics. We felt that their inclusion would detract from the results of the other farm-level and farmer-specific variables. However, they may be worthy of inclusion in subsequent analyses of adoption of other forms of GM technology.*

Table 2. Results of the probit model on the probability of GM crop adoption.

Variable	Coefficient	Standard error	Z statistic
Constant	-0.4783	0.5410	-0.88
Size	0.0075*	0.0034	2.21
Size2	-0.0001	0.0001	-1.48
Land	-0.4851	0.3195	-1.52
Rent	-0.0085	0.1260	-0.07
Profit	0.0021	0.0025	0.82
Age	-0.0056	0.0048	-1.16
Educ	0.0534	0.0534	1.00
Aged	0.3903***	0.1157	3.37
Ofarm	-0.1661	0.1201	-1.38
Risk	-0.2553	0.2023	-1.26
Soil1	0.4221**	0.1911	2.21
Soil2	0.5005***	0.1926	2.60
Dspec	-0.5171***	0.2046	-2.53
Doth	-0.7777***	0.2232	-3.48
Crear	-0.3264	0.2166	-1.51
Coth	-0.3093	0.2100	-1.47
Sheep	-0.4119**	0.2333	-1.77
Loglikelihood	-470.2789		
LR $chi^2(15)$	82.99		
Pseudo R2	0.0811		

**** significant at the 1% level, **significant at the 5% level, *significant at the 10% level*

Table 3. Marginal effects of the probit model on the probability of GM crop adoption.

Variable	Coefficient	Standard error	Z statistic
Constant	0.2811		
Size	0.0025	0.0012	2.21
Size2	-6.17e-06	0.0000	-1.48
Land	-0.1636	0.1077	-1.52
Rent	0.0029	0.0425	-0.07
Profit	0.0007	0.0009	0.82
Age	-0.0019	0.0016	-1.16
Educ	0.0180	0.0180	1.00
Aged	0.1293	0.0374	3.46
Ofarm	-0.0548	0.0387	-1.18
Risk	-0.0802	0.0586	-1.37
Soil1	0.1407	0.0625	2.25
Soil2	0.1735	0.0677	2.56
Dspec	-0.1614	0.0584	-2.77
Doth	-0.2091	0.0445	-4.70
Crear	-0.1037	0.0643	-1.61
Coth	-0.0980	0.0621	-1.58
Sheep	-0.1247	0.0621	-2.01

tenure variables become insignificant.[8] The profit variable is also insignificant in determining adoption behaviour, though it has the expected positive sign. Once farm size is controlled for, the profit variable is insignificant, but the variable was positive and significant in its respective stepwise regression. This result highlights the importance of farm size in explaining adoption behavior while also illustrating how it may dominate other farm-level characteristics.

While a negative sign was expected for the age variable, the variable is in itself insignificant throughout the model. It was assumed that age would be negatively associated with the adoption of GM crops, which was the result of a stepwise regression. The education dummy variable, another proxy for the human capital of the farmer, is also insignificant throughout the model, although the variable had a significantly positive effect on adoption in a stepwise regression. This result indicates that once other human capital factors such as experience of the farm operator are accounted for, education becomes insignificant.

Indeed the agricultural education level of the farmer is a highly significant variable and indicates that farm operators with higher levels of agricultural education are more receptive to new ideas and more willing to investigate alternative farming systems, such as the adoption of GM crops. The marginal effects in Table 3 indicate that a one-unit change in the agricultural education variable means that farmers who have completed formal agricultural education are 13% more likely to grow GM crops than those who have not, all other things being equal.

The results for the *Ofarm* variable were surprising. The variable has a negative sign, which was unexpected, and furthermore has no significance in determining adoption of GM technology. As discussed previously, if GM technology results in greater flexibility in crop management then adopters of the new technology would have an opportunity to spend more time in employment off the farm, and thus a positive effect was expected. However, this variable was insignificant throughout the model, including the stepwise regression stage, and was

8. *Landrent, a continuous variable representing the amount of land rented as a percent of UAA, was also used in some regressions. This variable returned a positive and significant result. However, this was almost certainly a size rather than a tenure effect, as this variable is correlated with the size variable. Accordingly, the renter dummy was incorporated into the final specification of the model to compensate for this.*

also not significantly correlated with the dependent variable. This result may reflect a lack of information of the benefits associated with GM crops, especially HT crops, but may also reflect the relatively small size of Irish farms compared to those of other countries. HT crops are expected to provide greater flexibility in crop management than conventional crops, but the benefits will likely accrue to a greater extent to larger farmers than to those of a smaller size.

The *Risk* variable also has no significance in the final specification of the model once other individual farm and farmer characteristics, such as those discussed above, are controlled. The variable also has a negative sign, which is contrary to expectations.

The results for the *Soil1* and *Soil2* dummy variables demonstrate that both variables have a positive effect on the adoption decision. This is further illustrated in the marginal effects. A one-unit change in the *Soil1* variable indicates that farmers with access to *Soil1* are 14% more likely than other farmers to grow GM crops, all other things being equal, while farmers with access to *Soil2* are 17% more likely. These results both adhere to the assumptions made in the earlier in the article.

The five sectoral dummy variables all have a negative effect on the decision to grow GM crops, with the variables for specialist dairy farmers (*Dspec*), dairy and other farmers (*Doth*), and sheep farmers (*Sheep*) being significant. Farmers in these production systems appear to be less likely than specialist tillage farmers to grow GM crops. This is clearly emphasized in the marginal effects. For example, specialist dairy farmers are 16% less likely to grow GM crops than other farmers, all other things being equal. The corresponding figures for dairy and other farmers and mainly sheep farmers illustrate that farmers in these sectors are 21% and 12% less likely than other farmers to grow GM crops, respectively. Existing specialist crop farmers can be assumed to have greater knowledge of the likely benefits associated with the adoption of new crops and technologies than other farmers predominantly engaged in other agricultural production systems.

Conclusions

The primary purpose of this study was to determine what specific individual and farm-level characteristics influence the willingness of farmers to investigate the adoption of GM technology in Ireland. Innovations theory was assumed to be the framework around which to develop a model, and a probit regression was used to determine the influence of specific selected explanatory variables (chosen from Teagasc National Farm Survey data) on the decision to adopt. The results demonstrated that both farm and farmer-specific characteristics are important in the adoption process.

Farm size had a significant and positive effect on the decision to adopt, indicating that larger farmers are more likely to consider adoption of new GM technology than smaller farmers. This result is in accordance with similar ex-post adoption studies on Bt and HT corn adoption in the United States (Fernandez-Cornejo & McBride, 2002; Marra et al., 2001). None of the land-tenure variables—representing the proportion of land owned or whether the farmer rented additional acreage—had any significance in the model once farm size was accounted for. In addition, the profitability variable was also insignificant. The tenure variables and farm profitability are correlated with farm size. Table 2 illustrates that both the *Rent* and profitability variables are positively correlated with farm size, while *Land* is negatively correlated. This result could be interpreted that farm size is a more reliable estimator of expected future earnings than the current level of farm income. The finding that tenure has no effect on the likelihood of adoption is supportive of Bulenta's and Hoiberg's (1983) study of the adoption of conservation tillage.

Contrary to expectations, both the age and education variables were insignificant in the model. The result for the age variable is supportive of previous research by Daberkow and McBride (2003) and Boz and Akbay (2005), who also found an insignificant relationship between age and the adoption decision in their respective studies, though it is contradictory to the theory of innovations (Rogers, 1995). Boz and Akbay (2005) suggested that this may be due to the perceived economic benefit attributed to the particular innovation. For example, if Irish farmers perceive an economic benefit from the adoption of a new technology they may be more likely to try the innovation regardless of their respective ages. The result for the education variable is contrary to the findings of several other studies of adoption behavior. For example, education of the farmer was found to have a positive effect on adoption of GM oilseed rape in Germany (Breustedt et al., 2008) and on Bt and HT corn adoption in the United States (Fernandez-Cornejo & McBride, 2002; Marra et al., 2001). The inclusion of the agricultural education variable in the model may help explain this result.

The variable that measured the agricultural education of the farmer was highly significant throughout each stage of the model and also had a positive and significant effect on adoption of GM technology. The ability to adapt new technologies for use on a specific farm, the farmers' human capital, has been found to influence the adoption decision (Daberkow & McBride, 2003). Farmers with formal agricultural education can be assumed to have the experience necessary to cultivate GM crops successfully. Accordingly the positive and significant effects for this experience variable were as expected.

Contrary to expectations neither the *Ofarm* or *Risk* variables had any significance in the final specification of the model. The discussion in the *Data and Variables* section of this article highlighted how the *Ofarm* variable had no significance in a stepwise regression and how the variable was not statistically significantly correlated with the dependent variable. Data constraints did not allow for the generation of more representative variables for the risk preferences of farmers. Diederen et al. (2003) suggested that a possible explanation for the insignificance of the profitability/solvency variable in determining adoption behavior in their Dutch study was that solvency may rather be an indicator of farmer's attitude towards risk than of financial condition. Table 2 shows that the *Risk* variable is positively correlated with the profitability variable, which may explain the insignificant result. Further analysis may warrant the inclusion of other factors so as to better capture the risk profile of Irish farmers.

Both the *Soil1* and *Soil2* variables had positive effects in determining the adoption of GM technology. These results were as expected, as tillage production typically occurs on high-soil-quality land. Specialist tillage farmers were assumed to be more likely to favor the adoption of GM crops than farmers in other agricultural systems, as they were assumed to have a greater awareness of the potential attributes associated with GM crops. It was assumed that if any other farmer types would indicate a preference towards cultivating GM crops it would be those involved in dairy production. However, the results indicate that this is not the case. As dairy production in Ireland is currently the most profitable agricultural system, this result is not altogether unexpected since switching to tillage and to the adoption of GM crops could be seen as a highly risky venture for existing dairy farmers.

In summation, the results of this analysis indicate which farmer demographic is likely to provide the early adopters of GM crops should they become available for cultivation in Ireland. These are farmers with large farm acreage who are specialist crop farmers and who have formal agricultural education and access to high-quality soils. The findings of this research have indicated which farmers are among the most likely adopters of the new technology. Accordingly, this research should be of considerable assistance to policymakers in helping them develop their guidelines to facilitate the specific target group. Furthermore, policymakers and extension agents will now be assisted in distinguishing between farms regarding their likelihood of technology adoption.

References

Alexander, C., & Van Mellor, T. (2005). Determinants of corn rootworm resistant corn adoption in Indiana. *AgBioForum*, *8*(4), 197-204. Available on the World Wide Web: http://www.agbioforum.org.

Anemiya, T. (1985). *Advanced econometrics*. Cambridge, MA: Harvard University Press.

Boz, I., & Akbay, C. (2005). Factors influencing the adoption of maize in Kahramanmaras province of Turkey. *Agricultural Economics*, *33*, 431-440.

Breustedt, G., Muller-Scheesel, J., & Latacz-Lohmann, U. (2008). Forecasting the adoption of GM oilseed rape: Evidence from a discrete choice experiment in Germany. *Journal of Agricultural Economics*, *59*(2), 237-256.

Bulenta, G., & Hoiberg, E. (1983). Factors affecting farmers' adoption of conservation tillage. *Journal of Soil and Water Conservation*, *May-June*, 281-284.

Daberkow, S., & McBride, W. (2003). Farm and operator characteristics affecting awareness and adoption of precision agriculture technologies in the US. *Precision Agriculture*, 4, 163-177.

Demont, M., Cerovska, M., Daems, W., Dillen, K., Fogarasi, J., Mathijs, E., et al. (2008). Ex ante impact assessment under imperfect information: Biotechnology in new member states of the EU. *Journal of Agricultural Economics*, *59*(3), 463-486.

Diederen, P., Van Meijl, H., Wolters, A., & Bijak, K. (2003). *Innovation adoption in agriculture: Innovators, early adopters and laggards* (Cahiers D'économie et Sociologie Rurales no. 67). France: INRA Social Sciences, Agriculture and Food, Rural Development and Environment.

El-Osta, H., & Morehart, M. (1999). Technology adoption decisions in dairy production and the role of herd expansion. *Agriculture and Resource Economics Review*, *28*(1), 84-95.

Feder, G., & O'Mara, G. (1981). Farm size and the diffusion of green revolution technology. *Economic Development and Cultural Change*, *30*, 59-76.

Feder, G., Just, R., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change*, *33*(2), 255-298.

Fernandez-Cornejo, J., Daberkow, S., & Huang, W-H. (1994). The adoption of IPM techniques by vegetable growers in Florida, Michigan and Texas. *Journal of Agricultural and Applied Economics*, *26*(1), 158-172.

Fernandez-Cornejo, J., & McBride, W. (2002). *Adoption of bioengineered crops* (Agricultural Economics Report No. 810). Washington, DC: US Department of Agriculture Economic Research Service (USDA ERS).

Fernandez-Cornejo, J., Klotz-Ingram, C., & Jans, S. (2002). Farm-level effects of adopting herbicide-tolerant soybeans in the USA. *Journal of Agricultural and Applied Economics*, *34*(1), 149-163.

Fernandez-Cornejo, J., Hendricks, C., & Mishra, A. (2005). Technology adoption and off-farm household income: The case of herbicide-tolerant soybeans. *Journal of Agricultural and Applied Economics*, *37*(December), 549-63.

Fernandez-Cornejo, J., Mishra, A., Nehring, R., Hendricks, C., Southern, M., & Gregory, A. (2007). *Off-farm income, technology adoption, and farm economic performance* (Agricultural Economics Report No. 36). Washington, DC: USDA ERS.

Flannery, M-L., Thorne, F., Kelly, P., & Mullins, E. (2004). An economic cost-benefit analysis of GM crop cultivation: an Irish case study. *AgBioForum*, *7*(4), 149-157. Available on the World Wide Web: http://www.agbioforum.org.

Griliches, Z. (1957). Hybrid corn: An exploration in the economics of technological change. *Econometrica*, *25*, 501-522.

Hoff, K., Braverman, A., & Stiglitz, J. (1993). *The economics of rural organisation: Theory, practice and policy.* New York: Oxford University Press.

James, C. (2007). *Global status of commercialized biotech/GM crops: 2007* (ISAAA Brief No. 37). Ithaca, NY: International Service for the Acquisition of Agri-Biotech Applications (ISAAA). Available on the World Wide Web: http://www.isaaa.org/purchasepublications/itemdescription.asp?ItemType=BRIEFS&Control=IB037-2007.

Just, R., Zilberman, D., & Rausser, G. (1980). A putty-clay approach to the distributional effects of new technology under risk. In D. Yaron & C. Tapiero (Eds.), *Operations research in agriculture and water resources*. New York: North Holland Publishing Company.

King, R., & Rollins, T. (1995). Factors influencing the adoption of a nitrogen testing program. *Journal of Extension*, *33*(4). Available on the World Wide Web: http://www.joe.org/joe/1995august/rb2.php.

Marra, M., & Carlson, G. (1987). The role of farm size and resource constraints in the choice between risky technologies. *Western Journal of Agricultural Economics*, *12*(2), 109-118.

Marra, M., Hubbell, B., & Carlson, G. (2001). Information quality, technology depreciation, and Bt cotton adoption in the Southeast. *Journal of Agricultural and Resource Economics*, *26*(1), 158-175.

May, M. (2003). Economic consequences for UK farmers of growing GM herbicide tolerant sugar beet. *Annals of Applied Biology*, *142*, 41-48.

Rahm, M., & Huffman, W. (1984). The adoption of reduced tillage: The role of human capital and other variables. *American Journal of Agricultural Economics*, *66*(4), 405-413.

Rogers, E. (1995). *Diffusion of innovations* (4th ed.). New York: The Free Press.

Sunding, D., & Zilberman, D. (2001). The agricultural innovation process: Research and technology adoption in a changing agricultural sector. In B. Gardner & G. Rausser (Eds.), *Handbook of agricultural economics, Volume 1*. Amsterdam: North Holland Publishing Company.

Teagasc. (2007, August). *National farm survey 2006*. Athenry County, Galway, Ireland: Teagasc Farm Surveys Department, Rural Economy Research Centre.

Teagasc. (2008, July). *National farm survey 2007* Athenry County, Galway, Ireland: Teagasc Farm Surveys Department, Rural Economy Research Centre.

Vanslembrouck, I., van Huylenbroeck, G., & Verbeke, W. (2002). Determinants of the willingness of Belgian farmer's to participate in agri-environmental measures. *Journal of Agricultural Economics*, *53*(3), 489-511.