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Best Management Practices to Enhance Water Quality: Who is Adopting Them?

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This study investigates the determinants affecting producers' adoption of some Best Management Practices (BMPs). Priors about the signs of certain variables are explicitly accounted for by testing for inequality restrictions through importance sampling. Education, gender, age, and on-farm residence are found to have significant effects on the adoption of some BMPs. Farms with larger animal production are more apt to implement manure management practices, crop rotation, and riparian buffer strips. Also, farms with larger cultivated acres are more inclined to implement herbicide control practices, crop rotation, and riparian buffer strips. Belonging to an agro-environment club has a positive impact for most BMPs.

Key Words: adoption, Bayesian analysis, best management practices, priors, runoff, water quality

JEL Classifications: Q12, Q25, C11

For a long time in the province of Quebec (Canada), water quality issues have been neglected and as a result severe environmental problems arose (e.g., well contamination). A moratorium on the development of new hog production facilities and expansion of capacity was imposed between 2002 and 2005. The moratorium slowed down expansion of agricultural activities in problem and nonproblem areas, but it failed to address the water quality issues in areas with acute problems. The lesson from this episode is that the problems tend to be local (watershed specific) and that policies ought to be applied at that level. Subsequent to the moratorium, new regulations were imposed and it has become a public policy priority to find ways to mitigate negative environmental externalities arising from agricultural activities. This is especially true in regions like the Chaudière region where there is a high concentration of hog, beef, and dairy production facilities. In this context, it seems most pertinent to analyze factors conditioning the adoption of Best Management Practices (BMPs) at the watershed level and to use this information to design programs to achieve a target adoption level set in relation to the severity of the water quality problems in the watershed.

The objective of this study is to ascertain the impact of socio-economic factors, farm characteristics, and operational factors on the probability of BMP adoption in the greater Chaudière region in Quebec. Water quality degradation

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brought about by agricultural production is of great concern in this region. This is why significant efforts are made to encourage the adoption and implementation of BMPs, such as crop rotation, surface runoff control, reduced herbicide use, and solid and liquid manure management. It is believed that BMPs are likely to improve water quality by limiting leaching and runoff of chemicals and sediments.

The recommended practice of gradually introducing perennial crops, such as alfalfa, into crop rotations is meant to protect surface soils and enhance nutrient uptake while improving soil structure, thereby improving water quality. For example, harvested alfalfa can export twice the volume of nitrates as corn for the same amount of dry matter removed. Also, the use of annual crops in rotation with cereals should help break the pest cycle, while providing both positive environmental and economic benefits. Surface runoff control is needed because sediment and contaminant transport from agricultural soils to ditches and streams is exacerbated locally by steep stream bank and ditch side slopes, continuous annual row cropping, and a general lack of erosion control methods. This problem is tackled through the establishment of riparian buffer strips, the reduction of the side slope of stream and ditch banks and planting of shrubs and trees along them, and the establishment of grassed waterways. The reduction of herbicide use is coordinated through a weed control program which features a decision support system developed by Agriculture and Agri-Food Canada.[1] Manure management entails applying solid and liquid manure using a low-ramp spreader equipped with trail hoses. This practice aims at reducing nitrogen loss through ammonia volatilization. In addition, postemergence application of liquid manure should optimize plant nitrogen and phosphorus use efficiency, further reducing the environmental risks of water and air pollution.

Agricultural producers are likely to hold heterogeneous beliefs regarding the costs and benefits of BMPs and as such are likely to have different probabilities of adoption. Our analysis is designed to shed some light on the factors conditioning adoption and hence provide valuable information for the design of government programs encouraging adoption. Our analysis builds on a rich literature pertaining to technology or practice adoption by agricultural producers (e.g., Adesina and Chianu, 2002; Banerjee et al., 2008; El-Osta and Morehart, 1999; Gillespie, Kim, and Paudel, 2007; Kim, Gillespie, and Paudel, 2005; Paudel et al., 2008; Rahelizatovo and Gillespie, 2004; Rahm and Huffman, 1984; Van Vuuren, Larue, and Ketchabaw, 1995; Ward et al., 2008). The empirical results can be used to tailor incentives and promotional efforts to achieve BMP adoption objectives.

The rest of the paper is organized as follows. The next section presents an overview of the theoretical foundation for our adoption models. The following section describes the survey that was implemented to generate our data and provides descriptive statistics of our dataset. This is followed by a section devoted to the discussion of the estimation results and the marginal effects of socio-economic variables, farm characteristics, and operational variables on the probability of BMP adoption. Policy implications and concluding remarks are presented in the last sections.

Conceptual Framework: A Random Utility Approach

Developing and implementing BMPs' policies require a thorough understanding of the factors affecting their adoption decision by agricultural producers. Rahm and Huffman (1984) and Adesina and Zhinna (1993) developed a general model based on the maximization of a producer's utility to explain the adoption of a given practice or technology. Let an arbitrary producer's decision to adopt a given BMP be denoted by *bmp* with $bmp = 1$ when the BMP is adopted and $bmp = 0$ when it is not. The utility of producer i has a deterministic and a stochastic component such that:

$$(1) \qquad U_i^{bmp} = \alpha_i^{bmp} F(H_i, G_i, M_i) + e_i^{bmp}$$

where H_i is a vector of socio-economic factors specific to the producer, G_i is a vector of farm

[1] Some of Agriculture and Agri-Food Canada's pesticide risk management projects are described at: http://www4.agr.gc.ca/AAFC-AAC/display-afficher.do?id=1187353833869&lang=eng.

attributes, M_i is a vector of variables associated with management and operational characteristics, α_i^{bmp} is a vector of coefficients associated with the adoption of the BMP, and e_i^{bmp} is an error term which embodies unobservable factors conditioning adoption. Given the random aspect of the utility, the producer adopts a BMP when $y_i^* \equiv U_i^1 - U_i^0 > 0$ where y_i^* is a latent (nonobserved) variable. Accordingly, the probability for a producer to adopt a BMP can be represented as follows:

$$\begin{aligned}
\Pr\left(y_i^* > 0\right) &= \Pr\left(\left(\alpha_i^1 F(H_i, G_i, M_i) + e_i^1\right)\right. \\
&\qquad \left. - \left(\alpha_i^0 F(H_i, G_i, M_i) + e_i^0\right) > 0\right) \\
&= \Pr\left(\left(e_i^1 - e_i^0\right) > - F(H_i, G_i, M_i)\right. \\
&\qquad \left. \times \left(\alpha_i^1 - \alpha_i^0\right)\right) \\
&= \Pr(\varepsilon_i > - F(H_i, G_i, M_i)\beta_i) \\
&= \Phi(X_i' \beta_i)
\end{aligned} \tag{2}$$

where $\beta_i = \left(\alpha_i^1 - \alpha_i^1\right)$ is a vector of coefficients, X_i is a vector of explanatory variables, ε_i is an error term assumed to be normally distributed, and $\Phi(\cdot)$ is the cumulative normal distribution function.[2]

Data Collection and Description

Data Collection

After consulting with representatives from the provincial ministry of agriculture (*Ministère de l'Agriculture, des Pêcheries et de l'Alimentation du Québec* or MAPAQ) regarding data on adoption of BMPs, it was concluded that existing datasets were either too small, too incomplete, or not enough compatible with one another to support the intended econometric analysis. Hence, data had to come from a survey of a sufficiently large pool of producers to generate enough observations. Our population of interest is made up of farms located in the Chaudière watershed in Quebec. We targeted hog, beef, and dairy producers. These producers also grow crops on their land (e.g., hay, cereals) and they account for the bulk of agricultural receipts in the area.[3] The coordinates of the producers were provided by MAPAQ upon authorization from the *Commission on Information Access*.

The survey was implemented between May and September of 2007.[4] The year of reference used in our questionnaire is 2006. The pretesting of the questionnaire was done in March of 2007 and the initial mailing was done early in May of 2007. The survey was sent to 1,319 producers. Two reminders followed over the next month and a second questionnaire mailing was done early in July of 2007 to increase the response rate. From the mailings, a total of 378 questionnaires were returned for a response rate of 28.7%. Some questionnaires were discarded when too many questions were unanswered and/or when the producer claimed to be exclusively engaged in animal production (i.e., not producing any crop). Consequently, the final sample consisted of 269 observations.

In our sample, the percentage of producers claiming to raise beef cattle and dairy cows account for 59.5% and 52.9%, respectively as many do both. Meanwhile, the percentage of hog producers is comparatively smaller at 20.8%.[5] However, these hog producers marketed a total of 197,000 hogs compared with 8,700 head for beef producers. The dairy

[2] In many empirical applications, the distribution is assumed to be logistic (e.g., Adesina and Chianu, 2002; Van Vuuren, Larue, and Ketchabaw, 1995). Amemiya (1981) showed that the results are robust to the choice of a distribution (logistic or normal).

[3] Producers whose main source of income is maple syrup production were purposely excluded from our sample. For them, BMPs considered in our analysis are irrelevant. Some producers in our sample produce maple syrup, but it is a side operation, not their main business.

[4] We had hoped to start mailing questionnaires in March but it took longer than expected to get the necessary authorization from the Commission on Information Access. To encourage producers to fill the questionnaire, we made a charitable donation of $20 per completed questionnaire to a well-known local organization that awards scholarships to farm kids.

[5] We do not have the exact proportions of hog, dairy, and beef farms for the whole population as the list of addresses we received from MAPAQ did not have information about the activities of the farms. However, data from MAPAQ regarding a portion of the population, the Beaurivage sub-watershed, reveals proportions that are quite close to the ones computed from our sample. Therefore, even though we did not use a weighting scheme in computing descriptive statistics and in our regressions, we are confident in the representativeness of our sample.

Table 1. Summary Statistics of Variables Used in the Adoption Analysis

	Mean	Standard Deviation	Minimum	Maximum
CROPROT (binary variable)	0.66	0.47	0	1
RIPBUF (binary variable)	0.57	0.50	0	1
HERBCONT (binary variable)	0.42	0.49	0	1
MANSOL (binary variable)	0.15	0.36	0	1
MANLIQ (binary variable)	0.45	0.50	0	1
AGE (years)	49.23	9.95	18	81
GENDER (binary variable)	0.04	0.21	0	1
EDUCATION (order variable)	2.31	1.04	1	5
RESFARM (binary variable)	0.88	0.32	0	1
PRODANIM (thousands of $)	272.95	371.61	0	3,489.98
PRODCROP (hundreds of acres)	1.24	1.41	0.01	11.21
MACHINERY (thousands of $)	142.58	124.19	1.79	798
BIOPROD (binary variable)	0.03	0.18	0	1
ENVCLUB (binary variable)	0.62	0.49	0	1
TELCOM (thousands of $)	1.33	1.73	0.05	15
PLABOR ($ per hour)	11.73	7.98	2.03	83.33
PHERB ($ per acre)	10.44	3.40	2.27	29.63
PFERT ($ per acre)	34.76	14.23	5.35	118.17

producers in our sample owned a total of 5,600 dairy cows. Dairy, beef, and hog farms typically grow crops (corn, hay, alfalfa, pulses, and other cereals). The total acreage cultivated with crops by our respondents amounted to 33,380 acres.

The BMP Variables

The most common specification of the dependent variable in adoption models is through binary variables (e.g., Adesina and Chianu, 2002; Banerjee et al., 2008; Gillespie, Kim, and Paudel, 2007; Kim, Gillespie, and Paudel, 2005; Paudel et al., 2008). The dependent variables reflect binary choice sets by taking the value of one when the agent (producer) adopts the technology or practice and zero otherwise. There are five BMP binary dependent variables. The summary statistics of the BMP variables are presented in Table 1. The implementation of crop rotation cycles is captured through a binary variable denoted by *CROPROT* that takes the value of one when crop rotation cycles are practiced and zero otherwise.[6] In our sample, 66% of the respondents claimed to implement crop rotation cycles on their cultivated land. The establishment and maintenance of a riparian buffer zone is denoted by *RIPBUF*. It takes a value of one when a riparian buffer zone larger than one meter is established and maintained and zero otherwise. The percentage of the respondents who maintained a buffer zone larger than one meter was 57%.

The adoption of herbicide control and reduction measures is represented through the binary variable *HERBCONT* that takes the value of one when the producer controls herbicide drift and zero otherwise.[7] In our sample, 42% of the respondents claimed to implement one or more herbicide control and reduction measures. The BMP associated with the utilization of solid manure is specified through a binary variable denoted by *MANSOL*. It takes

[6] We found that some producers practice crop rotation on only a fraction of their cultivated land. In these cases, crop rotation is considered to be practiced if it covers over half of the cultivated land. The empirical results remain robust at alternative thresholds.

[7] The herbicide control and reduction practices cover: the application of herbicides when the wind is below the recommended threshold, the usage of low pressure hoses and/or a protecting screen around the hoses, the establishment of buffer zones without herbicide treatment, the implementation of a follow-up system to avoid double applications, spraying of only infested zones, the usage of injection systems to eliminate non-utilized mixes in the containers, and the application of lower concentrations than those recommended on the label.

the value of one when the solid manure is injected in the soil within 24 hours of the initial spreading and zero otherwise. The percentage of respondents who claimed to implement this practice was only 15%. Similarly, the BMP associated with the utilization of liquid and semiliquid manure is specified through a binary variable denoted by *MANLIQ* that takes the value of one when the injection is practiced and occurring within 24 hours of the initial spreading and zero otherwise. The percentage of respondents who implemented the injection practice for liquid and semiliquid manure was 45%.

The above statistics show that the percentage of farms that have adopted BMPs varies across BMPs. From a policy point of view, it is crucial to find out who is adopting the BMP practices and to design programs to encourage adoption. This is where our analysis can be useful because we can estimate probabilities of BMP adoption for different profiles of farms and farmers.

The Explanatory Variables

The summary statistics of the explanatory variables are also presented in Table 1. Several studies about the adoption of new technologies and practices in agriculture revealed that producer's socio-economic attributes play an important role (e.g., Adesina and Chianu, 2002; Banerjee et al., 2008; Kim, Gillespie, and Paudel, 2005; Nagubadi et al., 1996; Nkamleu and Adesina, 2000; Paudel et al., 2008; Rahm and Huffman, 1984; Ward et al., 2008). The age of the primary producer is represented by the variable *AGE*. The sign on the age variable is *a priori* ambiguous. It can be hypothesized that older producers are less likely to adopt BMPs because they are less inclined to plan over a long horizon (Gillespie, Kim, and Paudel, 2007; Potter and Lobley, 1992) and because they are less aware of the new agricultural practices (Kehrig, 2002). In contrast, it can be argued that older producers are more likely to adopt BMPs because of their experience with a wider range of practices (Le and Beaulieu, 2005). Also, producers with lower debt-equity ratios are more likely to adopt BMPs (Paudel et al., 2008). To the extent that older producers have lower debt-equity ratios, they might better afford BMPs. Clearly, the expected sign is ambiguous and as such statistical inference should be based on a two-tailed test. The average age of the respondents in our dataset is 49 years old, with observations ranging from 18 to 81. The gender of the primary producer is represented through the binary variable *GENDER* that takes the value of one when the primary producer is a woman. There is an argument that women have stronger environmental concerns then man (Zelezny, Chua, and Aldrich, 2000). Women are perhaps more concerned about the health of their family and neighbors and therefore they are potentially more inclined to adopt BMPs. However, there is little evidence to support this.[8] Women make up only 4% of the primary producers in our dataset.

The level of education is specified through the ordered variable *EDUCATION*. It takes the value of one when primary school is attained, two when secondary school is attained, three for a technical school degree, four for a college degree, and five for a university degree.[9] As BMPs require good management and decisions making skills to obtain optimal results, it can be conjectured that education attainment of the primary producer is likely to significantly influence the decision to adopt a BMP (Rahelizatovo and Gillespie, 2004; Gillespie, Kim, and Paudel, 2007; Paudel et al., 2008; Ward et al., 2008). The average of this ordered variable centers between technical and college degrees. The residence location of the primary producer is captured through a binary variable denoted by *RESFARM* that takes a value of one when the residence is on farm ground and zero

[8] Gillespie, Kim, and Paudel (2007) found that men were more likely than women to adopt many erosion and sediment control BMPs.

[9] Alternative specifications of the education variable (e.g., through a binary variable that takes the value of one when the primary producer holds at least a technical school diploma or through several category-specific binary variables which allows for non-monotonic effects) generated empirical evidence that confirmed the robustness of our inferences regarding the impact of education on BMP adoption.

otherwise. The on-farm residence reflects higher involvement in farm management and health concerns for family and neighbors that are likely to increase sensitivity to local water quality issues. Therefore, residing on farm ground is expected to be associated with higher probability of BMP adoption. In our dataset, the percentage of primary producers that reside on farm ground is 88%.

The second set of explanatory variables consists of farm attributes. It is expected that larger farms are more likely to adopt environmental practices and new technologies due to economies of scale (Feder, Just, and Zilberman, 1985; Hindsley, 2002), less restrictive liquidity constraints, and bigger resources (El-Osta and Morehart, 1999; Rahelizatovo and Gillespie, 2004; Gillespie, Davis, and Rahelizatovo, 2004), and also because they attract greater public scrutiny (Le and Beaulieu, 2005). In this study, the farm size is represented by two size variables: area of cultivated land (in acres) and the value of animal production. These variables are denoted by *PRODCROP* and *PRODANIM*, respectively. In our dataset, the cultivated area per farm averaged 124 acres with observations ranging from a minimum of one acre to a maximum of 1,121 acres. The average value of animal production (i.e., live animals and milk) is $272,950 with observations ranging from a minimum of zero to a maximum of $3,489,980.

The effect of farm machinery and equipment is represented through the estimated value of owned and rented tractors, trucks, and other equipment such as tilling and harvesting equipment. This variable is denoted by *MACHINERY.* It is expected that higher ownership and utilization of machinery will or may facilitate the implementation of BMPs and hence positively impact on the probability of adoption. The average value of machinery in our dataset is $142,580 with a standard deviation of $124,190. The effect of having a certificate for biological/organic production is captured by the coefficient of the binary variable *BIOPROD* that takes the value of one when the farm has a certificate and zero otherwise. Only 3% of the respondents in our sample claimed to have a certificate for biological/organic production. The certificate of biological/organic production is assumed to have a positive effect on the adoption of BMPs. As expected, the data shows that producers certified for biological production do not apply herbicides in crop production.

The effect of belonging to an agro-environmental club is evaluated through the coefficient of the binary variable *ENVCLUB* that takes the value of one when the farm is a member and zero otherwise. The membership acts as an information source about agro-environmental issues and new agro-environmental practices. Therefore, it is expected to have a positive impact on the adoption of BMPs. The descriptive statistics show that 62% of the respondents had a membership in an agro-environmental club. Another variable that captures the accessibility of information is the level of annual expenditure on telecommunication services. The relevance of the telecommunication variable hinges on a positive correlation between the expenditure on telecommunication and information derived from telecommunication services. The *TELCOM* coefficient is expected to be positive because it is hypothesized that higher information accessibility would translate into a greater awareness about the benefits of BMPs. The average annual expenditure on telecommunication services was $1,330.

Finally, the vector of operational characteristics consists of: (1) the effective price of labor (i.e., dollars paid per hour) denoted by *PLABOR*;[10] (2) the effective price of fertilizers (i.e., fertilizers expenses per acre) denoted by *PFERT*; and (3) the effective price of herbicides (i.e., herbicides expenses per acre) denoted by *PHERB*. These variables enter the specification of BMP adoption equations whenever appropriate. Generally, it is expected that lower prices paid for inputs reflect good operational practices and facilitate adoption by relaxing financial constraints. However, higher prices for fertilizers and herbicides might encourage producers to consider concentration

[10] The effective price of labor is constructed by dividing the aggregate total labor cost (wages and benefits paid to family and non-family members) by the total number of hours worked by hired labor and family members.

reductions of chemical inputs. Furthermore, higher per unit labor costs might embody a premium for skills or experience that could positively impact the adoption of BMPs.[11] We conclude that the effects of prices on adoption are *a priori* ambiguous and might differ from one BMP to another. Thus, an empirical analysis is required to determine the sign and significance of input prices on BMP adoption.

The price of labor has an average of \$11.7 per hour with a standard deviation of \$8.0 per hour. The price of herbicides and fertilizers averaged \$10.4 per acre (with a standard deviation of \$3.4 per acre) and \$34.8 per acre (with a standard deviation of \$14.2 per acre), respectively. Variations in human capital and tightness in local labor markets might explain the relatively large standard deviation associated with the price of labor.[12]

Econometric Results

Inequality Restrictions in Single-Equation Estimations

The above discussion about the expected signs of various coefficients can most naturally be exploited by introducing priors on the effects of specific variables in the econometric estimation. "Priors are meant to reflect any information the researcher has before seeing the data" (Koop, 2003, p. 18) and as such can be grounded in theory or on any other information available to the researcher, like qualitative or quantitative outcomes that are consistently reported in the literature. Because our priors are defined in terms of signs, they entail estimation with inequality restrictions. Bayesian econometrics accommodates inequality restrictions in a most natural way and this is why it has been used in many contexts. For example, when monotonicity and concavity restrictions cannot be imposed parametrically in the estimation of demand systems, inequality constraints about the roots of matrices of substitution elasticities can be used to generate parameters and elasticities that are consistent with the so-called regularity conditions (e.g., Chalfant, Gray, and White, 1991; Larivière, Larue, and Chalfant, 2000). We rely on importance sampling and antithetic replications to impose inequality restrictions about the signs of certain coefficients and assess the plausibility of such restrictions. These concepts were developed by Geweke (1986, 1988, 1989) as extensions to standard Monte Carlo integration when it is difficult to take random draws directly from a posterior distribution. Because the approach is described in detail in virtually all Bayesian econometrics textbooks, we simply provide a brief intuitive description. The general idea behind importance sampling is to draw from another density and to weigh each draw so as to better approximate the posterior distribution of interest.[13] Let $\hat{\beta}$ represent the vector of coefficients obtained from an unrestricted estimation. Then, we can use the covariance matrix $V(\hat{\beta})$ to generate draws that are related to $\hat{\beta}$ as follows: $\beta_d = \hat{\beta} + \phi_d$. Antithetic replications simply entail generating $\beta_d = \hat{\beta} - \phi_d$. They provide a convenient tool to increase the number of draws while insuring a symmetric distribution (Geweke, 1988). The strategy to impose inequality restrictions consists of drawing sets of coefficients from an unrestricted multivariate distribution, to keep the sets of coefficients that are consistent with the inequality restrictions and to discard the others. Thus, a weight of one is given on sets of

[11] The adoption of BMPs may be cost-increasing or cost-reducing and may impact on the input mix. These issues can be best explored through a cost function with BMP shifters/dummies. The demand for labor could be obtained by applying Shepherd's lemma and the effect of BMPs could be directly assessed by comparing labor demand when different mixes of BMPs are adopted. Similarly, the effect of BMPs on cost could be assessed by computing predicted costs with and without BMPs. Such endeavor is beyond the scope of the current article.

[12] The cost share of labor, fertilizers, and herbicides from the total cost of labor, fertilizers, and herbicides averaged 72.3%, 21.1%, and 6.6%, respectively.

[13] To give some insight about importance sampling, Koop (2003, p. 79) defines a posterior $p(\beta|y)$ to be approximated by a density $q(\beta)$ that has the same mean but fatter tails. In this instance, importance sampling would weigh more draws taken from $q(\beta)$ that are close to the mean and weigh less draws farther away from the mean to better replicate $p(\beta|y)$.

coefficients consistent with the inequality restrictions and a weight of zero is given to the others. The mean and standard deviation for the inequality constrained coefficients can be computed directly from the resulting multivariate distribution. The coefficients that satisfy the inequality restrictions can be used to generate statistics about the distribution of marginal effects and probability differences which are easier to interpret than the coefficients of probit models. Since the mean and standard deviations of marginal effects are typically reported, the percentile method can be used to obtain confidence intervals from the sorted marginal effects. If S is the number of draws satisfying the inequality restrictions, then the lower and upper bounds are simply the $(0.025 * S)^{th}$ and $(0.975 * S)^{th}$ sorted marginal effects. For example, if $S = 10{,}000$, then the 250^{th} and $9{,}750^{th}$ sorted marginal effects are the lower and upper bounds. The precision with which the constrained coefficients are estimated can be enhanced by increasing the number of draws. The numerical standard error is routinely computed to guide the researcher in setting the number of draws. The plausibility of the restrictions can be assessed by computing the proportion of draws that are consistent with the restrictions. In this study, we used 10,000 antithetic replications or 20,000 draws. For each BMP, we report results for three sets of inequality restrictions (Models 1–3) and results from an unconstrained probit estimation (Model 4). The full set of inequality constraints restricts coefficients for education, on-farm residence, animal production, crop production, machinery, organic/biological production, and participation in an agro-environmental club. It is possible that one or more inequality restrictions are not supported by the data. This would make the probability for the whole set of restrictions very low even when the probabilities of other restrictions are very high. Therefore, it seems logical to test the plausibility of subsets of inequality restrictions. The second set restricts education and on-farm residence to have positive coefficients while the third set focuses on size effects (animal production, crop production, and machinery). Education and on-farm residence are nonpecuniary factors conditioning adoption. A better understanding of environmental issues and concerns about health of relatives and neighbors should motivate BMP adoption. Pecuniary incentives are also expected to matter and larger farms are expected to have a higher capacity to pay. The plausibility of a smaller set of restrictions can be compared with that of an alternative nonoverlapping smaller set of restrictions or to that of the larger set of restrictions. Through such comparisons, it will be easy to find out to what extent our results agree with various hypotheses motivated by theory and/or empirical regularity.

Tables 2A–E display the estimation results for the adoption of individual BMPs. The first four columns report coefficients with standard errors while the fifth column reports the 2.5% lower bounds, means, 97.5% upper bounds, and standard errors from the distribution of marginal effects for continuous explanatory variables and probability differences for dichotomous variables. We reported marginal effects for the model whose inequality restrictions were most likely. Table 2A presents the results for the adoption of riparian buffer strips. The proportion of draws that are consistent with all of the inequality restrictions imposed in Model 1 is 0.218 and its numerical standard error is 0.003, which implies that the proportion is measured with accuracy. We can then say with confidence that the inequality restrictions in Model 1 are observed with a probability of 22% which suggests that at least one inequality restriction is inconsistent with the data. In this instance, the fact that biological certification has low positive coefficients and large standard errors across restricted and unrestricted models makes it a likely cause for the high rejection rate of the larger set of inequality restrictions. The large standard errors, relative to the coefficients, imply that a negative coefficient was often drawn, thus forcing a rejection of the joint restrictions even when all of the other variables had coefficients with the "right" sign. It should be pointed out that there are very few producers in our sample that are certified organic/biological. The proportions of draws consistent with the inequality restrictions for Models 2 and 3 are respectively 0.606 and 0.832. We can interpret these proportions in terms of odds ratio by stating that the inequality restrictions in these two models are $0.606/0.394 = 1.54$ and $0.832/0.168 = 4.95$ times

Table 2A. Probit Estimation of Factors Conditioning the Adoption of Riparian Buffer Strips

	Model 1	Model 2	Model 3	Model 4	Model 3
	All Inequality Constraints Imposed	Inequality Constraints on *EDUCATION* and *RESFARM*	Inequality Constraints on *PRODANIM*, *PRODCROP*, and *MACHINERY*	No Inequality Constraints	Marginal Effects or Probability Differences
	$\hat{\beta}_i$	$\hat{\beta}_i$	$\hat{\beta}_i$	$\hat{\beta}_i$	$\phi(X'\hat{\beta})\hat{\beta}_i$
	Mean	Mean	Mean	Mean	$L_{0.025}$; Mean; $U_{0.975}$
Producer Characteristics:					
AGE	0.0328[a] (0.0092)	0.0334[a] (0.0092)	0.0343[a] (0.0093)	0.0341[a] (0.0093)	0.006; 0.013; 0.020 (0.004)
GENDER	0.7680[e] (0.4763)	0.7621[e] (0.4800)	0.7561[e] (0.4791)	0.7531[e] (0.4761)	−0.07; 0.22; 0.39 (0.12)
EDUCATION	0.2481[a] (0.0917)	0.2625[a] (0.0921)	0.2656[a] (0.0930)	0.2675[a] (0.0938)	−0.03; 0.10; 0.17 (0.04)
RESFARM	0.2653[e] (0.1902)	0.2612[e] (0.1889)	0.0797 (0.2903)	0.0784 (0.2882)	−0.17; 0.03; 0.25 (0.11)
Farm Characteristics:					
PRODANIM	0.0014[a] (0.0005)	0.0014[a] (0.0005)	0.0014[a] (0.0005)	0.0014[a] (0.0005)	0.00; 0.0005; 0.0009 (0.0002)
PRODCROP	0.1321[d] (0.0765)	0.1209[e] (0.0941)	0.1347[d] (0.0783)	0.1170 (0.0932)	0.004; 0.05; 0.12 (0.03)
MACHINERY	0.0014[d] (0.0008)	0.0014[e] (0.0009)	0.0015[d] (0.0008)	0.0014[e] (0.0009)	0.00; 0.0006; 0.0012 (0.0003)
BIOPROD	0.4407[e] (0.3323)	0.0402 (0.5462)	0.0149 (0.5448)	0.0326 (0.5468)	−0.39; −0.01; 0.31 (0.19)
ENVCLUB	0.4320[a] (0.1673)	0.4399[b] (0.1729)	0.4242[b] (0.1731)	0.4271[b] (0.1748)	−0.03; 0.16; 0.29 (0.07)
TELCOM	0.0746[e] (0.0456)	0.0584 (0.0583)	0.0584 (0.0580)	0.0595 (0.0582)	−0.021; 0.022; 0.065 (0.022)
Operational Variables:					
PLABOR	0.0028 (0.0124)	0.0027 (0.0125)	0.0018 (0.0125)	0.0026 (0.0128)	−0.009; 0.001; 0.012 (0.005)
PFERT	−0.0013 (0.0059)	−0.0021 (0.0060)	−0.0022 (0.0060)	−0.0021 (0.0059)	−0.005; −0.001; 0.004 (0.002)
PHERB	0.0065 (0.0276)	0.0073 (0.0275)	0.0081 (0.0274)	0.0076 (0.0278)	−0.021; 0.003; 0.022 (0.011)
Constant	−3.3461[a] (0.7334)	−3.3593[a] (0.7355)	−3.2691[a] (0.7475)	−3.2364[a] (0.7527)	
Observations	269	269	269	269	
	Prop = 0.218	*Prop* = 0.606	*Prop* = 0.832	*Pseudo-R^2* = 0.174	
	NSE = 0.003	*NSE* = 0.003	*NSE* = 0.003		

Notes: Standard errors are in parentheses. In Model 1, the inequality constraints are imposed on *EDUCATION, RESFARM, PRODANIM, PRODCROP, MACHINERY, BIOPROD,* and *ENVCLUB*. NSE is numerical standard error; Prop is proportion.

[a, b, c, d,] and [e] denote a two-tailed (one-tailed) significance level of 1% (0.5%), 2% (1%), 5% (2.5%), 10% (5%), and 20% (10%), respectively.

Table 2B. Probit Estimation of Factors Conditioning the Adoption of Herbicide Control

	Model 1	Model 2	Model 3	Model 4	Model 3
	All Inequality Constraints Imposed	Inequality Constraints on *EDUCATION* and *RESFARM*	Inequality Constraints on *PRODANIM*, *PRODCROP*, and *MACHINERY*	No Inequality Constraints	Marginal Effects or Probability Differences
	$\hat{\beta}_i$	$\hat{\beta}_i$	$\hat{\beta}_i$	$\hat{\beta}_i$	$\phi(X'\hat{\beta})\hat{\beta}_i$
	Mean	Mean	Mean	Mean	$L_{0.025}$; Mean; $U_{0.975}$
Producer Characteristics:					
AGE	−0.0028 (0.0084)	−0.0032 (0.0084)	−0.0046 (0.0087)	−0.0049 (0.0087)	−0.008; −0.001; 0.006 (0.003)
GENDER	−0.1195 (0.4076)	−0.1184 (0.4091)	−0.1016 (0.4060)	−0.1095 (0.4087)	−0.30; −0.03; 0.27 (0.15)
EDUCATION	0.0734[e] (0.0548)	0.0735[e] (0.0547)	0.0125 (0.0880)	0.0121 (0.0881)	−0.06; 0.01; 0.07 (0.03)
RESFARM	0.2745[e] (0.1953)	0.2708[e] (0.1933)	0.1313 (0.2839)	0.1225 (0.2831)	−0.17; 0.05; 0.24 (0.11)
Farm Characteristics:					
PRODANIM	0.0005[d] (0.0003)	0.0004 (0.0004)	0.0005[d] (0.0003)	0.0004 (0.0004)	0.00; 0.0002; 0.0004 (0.0001)
PRODCROP	0.2661[a] (0.0909)	0.2704[a] (0.0916)	0.2782[a] (0.0921)	0.2827[a] (0.0922)	0.04; 0.11; 0.18 (0.04)
MACHINERY	0.0018[c] (0.0008)	0.0018[c] (0.0009)	0.0017[c] (0.0008)	0.0017[d] (0.0009)	0.00; 0.0006; 0.0010 (0.0003)
ENVCLUB	0.3340[c] (0.1628)	0.3255[d] (0.1796)	0.3124[d] (0.1775)	0.3191[d] (0.1750)	−0.012; 0.112; 0.251 (0.067)
TELCOM	0.1022[c] (0.0504)	0.1001[d] (0.0555)	0.1007[d] (0.0551)	0.1032[d] (0.0558)	−0.003; 0.041; 0.083 (0.022)
Operational Variables:					
PLABOR	0.0034 (0.0123)	0.0036 (0.0124)	0.0048 (0.0124)	0.0051 (0.0124)	−0.007; 0.002; 0.011 (0.005)
PHERB	−0.0032 (0.0257)	−0.0032 (0.0251)	−0.0058 (0.026)	−0.0059 (0.0261)	−0.023; −0.002; 0.021 (0.012)
Constant	−1.5066[b] (0.5888)	−1.4671[b] (0.5940)	−1.1293[d] (0.6652)	−1.0932[d] (0.6662)	
Observations	260	260	260	260	
	Prop = 0.278	*Prop* = 0.359	*Prop* = 0.818	*Pseudo*-R^2 = 0.135	
	NSE = 0.003	*NSE* = 0.003	*NSE* = 0.003		

Notes: Standard errors are in parentheses. In Model 1, the inequality constraints are imposed on *EDUCATION*, *RESFARM*, *PRODANIM*, *PRODCROP*, *MACHINERY*, *BIOPROD*, and *ENVCLUB*. Farms having a certificate for biological/organic production are dropped from the sample as they, by definition, do not apply herbicides in crop production. This is why the *BIOPROD* variable is not included as an explanatory variable. NSE is numerical standard error; Prop is proportion.

[a, b, c, d,] and [e] denote a two-tailed (one-tailed) significance level of 1% (0.5%), 2% (1%), 5% (2.5%), 10% (5%), and 20% (10%), respectively.

Table 2C. Probit Estimation of Factors Conditioning the Adoption of Crop Rotations

	Model 1	Model 2	Model 3	Model 4	Model 3
	All Inequality Constraints Imposed	Inequality Constraints on *EDUCATION* and *RESFARM*	Inequality Constraints on *PRODANIM*, *PRODCROP*, and *MACHINERY*	No Inequality Constraints	Marginal Effects or Probability Differences
	$\hat{\beta}_i$	$\hat{\beta}_i$	$\hat{\beta}_i$	$\hat{\beta}_i$	$\phi(X'\hat{\beta})\hat{\beta}_i$
	Mean	Mean	Mean	Mean	$L_{0.025}$; Mean; $U_{0.975}$
Producer Characteristics:					
AGE	0.0165[d] (0.0099)	0.0170[d] (0.0092)	0.0181[d] (0.0093)	0.0180[d] (0.0093)	0.00; 0.006; 0.012 (0.003)
GENDER	−0.4404 (0.3913)	−0.4281 (0.3886)	−0.4384 (0.3878)	−0.4418 (0.3855)	−0.45; −0.16; 0.10 (0.14)
EDUCATION	0.1815[c] (0.0827)	0.2169[b] (0.0920)	0.2247[b] (0.0963)	0.2246[c] (0.0970)	0.012; 0.075; 0.142 (0.032)
RESFARM	0.2201[e] (0.1655)	0.2284[e] (0.1742)	−0.0079 (0.2905)	−0.0052 (0.2896)	−0.172; 0.004; 0.213 (0.095)
Farm Characteristics:					
PRODANIM	0.0012[b] (0.0005)	0.0013[a] (0.0005)	0.0013[a] (0.0005)	0.0013[a] (0.0005)	0.0001; 0.0004; 0.0007 (0.0002)
PRODCROP	0.1603[d] (0.0835)	0.1647[d] (0.0885)	0.1649[c] (0.0809)	0.1588[d] (0.0877)	0.007; 0.055; 0.110 (0.027)
MACHINERY	0.0011[e] (0.0007)	0.0012[e] (0.0009)	0.0014[d] (0.0008)	0.0013[e] (0.0009)	0.00; 0.0005; 0.0011 (0.0002)
BIOPROD	0.2853 (0.2239)	−0.2276 (0.4915)	−0.2478 (0.4911)	−0.2311 (0.4944)	−0.45; −0.12; 0.19 (0.17)
ENVCLUB	0.1301[e] (0.1017)	−0.0037 (0.1745)	−0.0221 (0.1748)	−0.0203 (0.1761)	−0.12; −0.01; 0.11 (0.06)
TELCOM	0.0261[e] (0.0201)	−0.0500 (0.0488)	−0.0483 (0.0486)	−0.0477 (0.0489)	−0.048; −0.018; 0.016 (0.016)
Operational Variables:					
PLABOR	−0.0326[a] (0.0121)	−0.0331[a] (0.0127)	−0.0344[a] (0.0124)	−0.0338[a] (0.0129)	−0.021; −0.011; −0.004 (0.004)
PFERT	0.0031 (0.0059)	0.0018 (0.0062)	0.0017 (0.0061)	0.0016 (0.0061)	−0.003; 0.001; 0.005 (0.002)
PHERB	−0.0388[e] (0.0301)	−0.0323 (0.028)	−0.0320 (0.0279)	−0.0316 (0.0284)	−0.03; −0.01; 0.01 (0.01)
Constant	−0.9622[e] (0.732)	−0.9435[e] (0.7125)	−0.7951 (0.7345)	−0.7826 (0.7361)	
Observations	269	269	269	269	
	Prop = 0.007	*Prop* = 0.487	*Prop* = 0.885	*Pseudo*-R^2 = 0.117	
	NSE = 0.001	*NSE* = 0.004	*NSE* = 0.002		

Notes: Standard errors are in parentheses. In Model 1, the inequality constraints are imposed on *EDUCATION*, *RESFARM*, *PRODANIM*, *PRODCROP*, *MACHINERY*, *BIOPROD*, and *ENVCLUB*. NSE is numerical standard error; Prop is proportion.

[a, b, c, d,] and [e] denote a two-tailed (one-tailed) significance level of 1% (0.5%), 2% (1%), 5% (2.5%), 10% (5%), and 20% (10%), respectively.

Table 2D. Probit Estimation of Factors Conditioning the Adoption of Solid Manure Management

	Model 1	Model 2	Model 3	Model 4	Model 2
	All Inequality Constraints Imposed	Inequality Constraints on *EDUCATION* and *RESFARM*	Inequality Constraints on *PRODANIM*, *PRODCROP*, and *MACHINERY*	No Inequality Constraints	Marginal Effects or Probability Differences
	$\hat{\beta}_i$	$\hat{\beta}_i$	$\hat{\beta}_i$	$\hat{\beta}_i$	$\phi(X'\hat{\beta})\hat{\beta}_i$
	Mean	Mean	Mean	Mean	$L_{0.025}$; Mean; $U_{0.975}$
Producer Characteristics:					
AGE	0.0028 (0.0118)	0.0064 (0.0091)	0.0043 (0.0114)	0.0061 (0.0113)	−0.003; 0.001; 0.005 (0.002)
GENDER	0.8330[b] (0.3843)	1.0821[a] (0.4189)	1.0394[b] (0.4196)	1.0690[b] (0.4200)	0.06; 0.32; 0.62 (0.14)
EDUCATOION	0.1548[d] (0.0903)	0.2075[c] (0.0995)	0.1673[e] (0.1071)	0.2002[d] (0.1059)	0.006; 0.040; 0.081 (0.018)
RESFARM	0.5851[d] (0.3060)	0.5915[d] (0.3267)	0.6130[d] (0.3748)	0.5341[e] (0.3763)	0.011; 0.075; 0.143 (0.033)
Farm Characteristics:					
PRODANIM	0.0007[b] (0.0003)	0.0011[a] (0.0003)	0.0008[a] (0.0003)	0.0010[a] (0.0003)	0.00; 0.0002; 0.0003 (0.0001)
PRODCROP	0.0423 (0.0371)	−0.0680 (0.0838)	0.0475 (0.0404)	−0.0681 (0.0840)	−0.041; −0.012; 0.017 (0.016)
MACHINERY	0.0017[c] (0.0008)	0.0025[a] (0.0009)	0.0023[a] (0.0008)	0.0025[a] (0.0009)	0.0002; 0.0005; 0.0008 (0.0002)
BIOPROD	0.7042[d] (0.4060)	0.6383[e] (0.4918)	0.6611[e] (0.4948)	0.6407[e] (0.4888)	−0.05; 0.18; 0.52 (0.15)
ENVCLUB	0.4858[c] (0.2473)	0.5183[c] (0.2454)	0.4906[c] (0.2468)	0.5167[c] (0.2462)	0.01; 0.09; 0.16 (0.04)
TELCOM	0.0509 (0.0449)	−0.1689[e] (0.1122)	−0.1710[e] (0.1128)	−0.1653[e] (0.1116)	−0.071; −0.032; 0.009 (0.022)
Operational Variables:					
PLABOR	0.0153[e] (0.0108)	0.0212[d] (0.0121)	0.0150[e] (0.0115)	0.0210[d] (0.0120)	−0.001; 0.004; 0.008 (0.002)
PFERT	0.0038 (0.0075)	0.0029 (0.0079)	0.0048 (0.0078)	0.0028 (0.0079)	−0.002; 0.001; 0.003 (0.002)
Constant	−3.4045[a] (0.8112)	−3.6229[a] (0.8393)	−3.4653[a] (0.8852)	−3.5279[a] (0.8749)	
Observations	269	269	269	269	
	Prop = 0.01	*Prop* = 0.892	*Prop* = 0.206	*Pseudo*-R^2 = 0.217	
	NSE = 0.001	*NSE* = 0.002	*NSE* = 0.003		

Notes: Standard errors are in parentheses. In Model 1, the inequality constraints are imposed on *EDUCATION*, *RESFARM*, *PRODANIM*, *PRODCROP*, *MACHINERY*, *BIOPROD*, and *ENVCLUB*. NSE is numerical standard error; Prop is proportion.

[a, b, c, d,] and [e] denote a two-tailed (one-tailed) significance level of 1% (0.5%), 2% (1%), 5% (2.5%), 10% (5%), and 20% (10%), respectively.

Table 2E. Probit Estimation of Factors Conditioning the Adoption of Liquid Manure Management

	Model 1	Model 2	Model 3	Model 4	Model 2
	All Inequality Constraints Imposed	Inequality Constraints on *EDUCATION* and *RESFARM*	Inequality Constraints on *PRODANIM*, *PRODCROP*, and *MACHINERY*	No Inequality Constraints	Marginal Effects or Probability Differences
	$\hat{\beta}_i$	$\hat{\beta}_i$	$\hat{\beta}_i$	$\hat{\beta}_i$	$\phi(X'\hat{\beta})\hat{\beta}_i$
	Mean	Mean	Mean	Mean	$L_{0.025}$; Mean; $U_{0.975}$
Producer Characteristics:					
AGE	−0.0067 (0.0092)	−0.0064 (0.0093)	−0.0066 (0.0093)	−0.0065 (0.0093)	−0.012; −0.003; 0.005 (0.004)
GENDER	0.9951[c] (0.4626)	0.9993[c] (0.4499)	1.0032[c] (0.4504)	0.9994[c] (0.4467)	0.05; 0.34; 0.53 (0.13)
EDUCATION	0.1901[c] (0.0832)	0.2065[b] (0.0846)	0.1912[c] (0.0866)	0.2041[b] (0.0869)	0.021; 0.082; 0.149 (0.033)
RESFARM	0.7496[a] (0.2857)	0.7312[b] (0.2891)	0.7605[a] (0.2951)	0.7247[b] (0.2972)	0.074; 0.265; 0.423 (0.091)
Farm Characteristics:					
PRODANIM	0.0015[a] (0.0004)	0.0017[a] (0.0005)	0.0016[a] (0.0004)	0.0017[a] (0.0004)	0.0003; 0.0007; 0.0011 (0.0002)
PRODCROP	0.0606[e] (0.0462)	−0.0021 (0.0802)	0.0611[e] (0.0465)	−0.0019 (0.0091)	−0.063; −0.001; 0.064 (0.031)
MACHINERY	0.0009[e] (0.0006)	0.0008 (0.0008)	0.0010[d] (0.0006)	0.0008 (0.0008)	−0.0003; 0.0003; 0.0009 (0.0003)
BIOPROD	0.7910[d] (0.4515)	0.7021[e] (0.5310)	0.6826[e] (0.5301)	0.7030[e] (0.5283)	−0.13; 0.24; 0.50 (0.17)
ENVCLUB	0.5136[a] (0.1747)	0.5363[a] (0.1779)	0.5243[a] (0.1782)	0.5354[a] (0.1781)	0.08; 0.21; 0.33 (0.07)
TELCOM	0.0320 (0.0258)	−0.0135 (0.0469)	−0.0156 (0.04687)	−0.0134 (0.0464)	−0.042; −0.005; 0.034 (0.019)
Operational Variables:					
PLABOR	−0.0009 (0.0107)	0.0021 (0.0113)	−0.0011 (0.0108)	0.0021 (0.0112)	−0.008; 0.001; 0.010 (0.004)
PFERT	0.0074 (0.0060)	0.0065 (0.0062)	0.0076 (0.0059)	0.0065 (0.0060)	−0.002; 0.003; 0.007 (0.003)
Constant	−2.1691[a] (0.6784)	−2.1002[a] (0.6714)	−2.1480[a] (0.6733)	−2.0856[a] (0.6764)	
Observations	269	269	269	269	
	Prop = 0.129	*Prop* = 0.981	*Prop* = 0.885	*Pseudo*-R^2 = 0.188	
	NSE = 0.002	*NSE* = 0.0035	*NSE* = 0.002		

Notes: Standard errors are in parentheses. In Model 1, the inequality constraints are imposed on *EDUCATION*, *RESFARM*, *PRODANIM*, *PRODCROP*, *MACHINERY*, *BIOPROD*, and *ENVCLUB*. NSE is numerical standard error; Prop is proportion.

[a, b, c, d,] and [e] denote a two-tailed (one-tailed) significance level of 1% (0.5%), 2% (1%), 5% (2.5%), 10% (5%), and 20% (10%), respectively.

more likely to hold than not. Thus there is strong support for the inequality restrictions on coefficients pertaining to "size effects" and moderate support for the inequality restrictions on education and on-farm residence. The unrestricted model has a Pseudo-R^2 of 0.17, and like the restricted models it has several coefficients that are statistically significant.

The coefficient for the age of the primary producer was not restricted because there was no definite prior motivated by theory or empirical regularity, to justify a sign restriction. The coefficient is positive and significant, emphasizing the effect of experience and perhaps a lower debt-equity ratio. The marginal effect of age on the likelihood of maintaining a riparian buffer zone implies that a 10-year increase in the age of the primary producer induces an increase in the probability of maintaining a riparian buffer zone by 13% when all variables are evaluated at their mean value. The coefficient for gender was not inequality-constrained, but it turned out to be greater than zero at the 6% level of significance (i.e., one-tailed test). The marginal effect tells us that a female primary producer is 22% more likely to establish and maintain a riparian buffer zone than a male primary producer. Education has a significant effect as a higher degree induces a 10% increase in the probability of adoption. The restricted and unrestricted coefficients on education are quite similar which means that the prior does not add very much new information to the data. The inequality constrained coefficients for residing on the farm are significant at the 8% level and quite different from the unconstrained ones which are much lower than their standard errors.[14] In this instance, the prior obviously adds new useful information. Revenue from animal production has a positive and significant coefficient. The marginal effect implies that the probability of adopting a riparian buffer zone increases by 5% for each additional \$100,000-increase in revenue from beef, hog, and dairy productions. The explanation is that large farms probably face higher pressure to implement riparian buffer zones. The coefficient on the number of acres of cultivated crop land is positive and significant at the 5% level (i.e., one-tailed test for Model 3). A 100-acre increase raises the likelihood of adopting a riparian buffer zone by 5%. The productive value of the land forgone to buffers is probably less of a concern for larger farms. The coefficient on machinery is positive and significantly so at the 3% level (i.e., one-tailed test for Model 3). The probability of establishing riparian buffer zones is expected to increase by 6%, but possibly as low as 0% or as high as 12%, for each \$100,000-increase in the value of machinery. The coefficient for membership in an agro-environmental club is positive and significant, constrained or not, at the 5% level. In fact, belonging to an agro-environmental club augments the probability of establishing and maintaining riparian buffer zones by 16%. Input price variables did not have a significant effect on the adoption of buffer strips. This outcome can be partly explained by the fact that the "cost" from the producer standpoint is essentially the lost net revenue from removing land from production to buffer zones. The riparian buffer may be perceived at very low cost to the producer, particularly when using input cost as a measure.

Table 2B presents the results for herbicide control and reduction measures. Extension efforts in recent years have encouraged the use of reduced concentrations of chemicals. Surprisingly, none of the socio-economic factors were found to have a significant effect in Model 3. The inequality restrictions on education and on-farm residence have a probability of only 36% while the "size restrictions" of Model 3 have a probability of 82% and hence are 4.55 times more likely to hold than not. Revenue from animal production has a positive and significant coefficient in Model 3. Thus, larger livestock producers are more likely to adopt herbicide control measures. The coefficient on the number of acres of cultivated crop land is positive and significant at the 1% level. A 100-acre increase raises the likelihood of adopting herbicide control practices by 11%. A \$100,000-increase in machinery increases the probability

[14] In cases involving a strong prior about the sign of a coefficient, a one-tail test must be used because the alternative hypothesis is one-sided.

of adopting herbicide control practices by 6%. Also, membership in an agro-environmental club increases the probability of adopting herbicide control by 11.2%; all else are equal. The telecommunication variable, which correlates with access to information, has a significant effect. A $1,000-increase in telecommunication expenses augments the probability of adoption by 4.1%. Input price variables did not have a significant effect, which could mean that such variables truly do not matter or that they embody offsetting effects. One might think that higher input prices reduce profit and might make BMP adoption less likely. Alternatively, higher input prices might induce producers to conduct an evaluation of their technology, input use, and management practices that could lead to BMP adoption.[15]

Table 2C reports the results pertaining to the adoption of crop rotation practices. The full set of inequality restrictions is less likely to hold (or has a much lower probability) than for the adoption of the two previous BMPs. As for the adoption of herbicide control, our prior about "size" finds much support from the data as these inequality restrictions holds with a probability of almost 89%. The positive and significant coefficient on the age of the primary producer highlights the effect of experience and wider exposure to various agricultural practices. The marginal effect indicates that an increase in the age of the primary producer by 10 years raises the likelihood of practicing crop rotation by 6.0%, when all variables are evaluated at their mean value. Education is another socio-economic variable that significantly impacts on the probability of adoption. Achieving a higher educational attainment increases the likelihood of adoption by 7.5%. The number of acres of cultivated land has a significant effect at the 2% level (one-tailed test, Model 3). A 100-acre increase in land endowment induces an increase in the likelihood of adopting crop rotation practices by 5.5%. The size of animal production has a significant effect at the 1% level. The marginal effect implies that the probability of adoption increases by 4% for each additional $100,000-increase in the value of animal and animal products produced on the farm. Machinery has a coefficient that is significant at the 4% level (i.e., one-tailed test, Model 3). The marginal effect of machinery implies that the probability of adoption increases by 5% for each additional $100,000-increase. The price of labor has a negative and significant coefficient at the 1% level. A $1 per hour increase in the price of labor reduces the probability of practicing crop rotation by 1.1%.

The results for the adoption of solid and liquid manure injection methods are presented in Tables 2D and 2E, respectively. In both cases, the inequality restrictions on education and on-farm residence finds much support with probabilities of 89% and 98%, respectively. Support for the inequality restrictions on the "size" coefficients differ widely as the probabilities that the restrictions be observed are 21% and 89%, but the unrestricted models for these two BMPs have similar *Pseudo*-R^2 values (0.22 versus 0.19). One interesting result is that a female primary producer is 32% and 34% more likely to adopt injection methods of solid and liquid manure than a male primary producer. Thus, women seem to have greater concerns for sanitation and the health of family members and neighbors. The coefficients on on-farm residence are again significant for both solid and liquid manure control practices. Reported marginal effects imply that residing on farm grounds increases the probability of adopting manure injection practices by 7.5% for solid manure and 26.5% for liquid manure. This outcome can also be partly explained by concern about odors in addition to sanitation and health concerns. Higher educational achievement raises the adoption likelihood by 4% for solid manure and 8.2% for liquid manure. A $100,000-increase in the value of animal products induces an increase in the probability of adoption by 2% for solid manure and 7% for liquid manure. These percentages suggest that larger farms face more, and/or are more responsive to, pressure to adopt BMPs; but the "size effect" is relatively small considering that the mean revenue from animal production is $272,950. The significance of the

[15] Higher fertilizer and herbicide prices might induce the adoption of "reduced doses" which make economic and environmental sense when field conditions allow them.

Table 3. Correlation Coefficients from Multivariate Probit Estimation

	Correlation Coefficient		Correlation Coefficient
(*CROPROT*, *RIBUF*)	−0.032 (0.126)	(*RIPBUF*, *MANSOL*)	0.163 (0.213)
(*CROPROT*, *HERBCONT*)	0.044 (0.138)	(*RIPBUF*, *MANLIQ*)	0.085 (0.129)
(*CROPROT*, *MANSOL*)	−0.139 (0.208)	(*HERBCONT*, *MANSOL*)	−0.001 (0.182)
(*CROPROT*, *MANLIQ*	0.020 (0.135)	(*HERBCONT*, *MANLIQ*)	0.101 (0.122)
(*RIPBUF*, *HERBCONT*)	0.088 (0.122)	(*MANSOL*, *MANLIQ*)	0.669[a] (0.184)

Notes: Standard errors are in parentheses.
[a] Denotes a significance level of 1%.

effect of machinery varies across models (e.g., Model 3 versus Model 2) when the adoption of liquid manure management is concerned, but is significant across models for solid manure management. Membership in an agro-environmental club is a significant variable and it increases the probability of adopting manure injection practices by 9% for solid manure and 21% for liquid manure. The coefficients on the biological/organic certification variable are positive and the confidence intervals for the marginal effects span mostly positive values. Having a biological/organic certificate of production increases the probability of adopting manure injection practices by 18% for solid manure and 24% for liquid manure. The higher marginal effects for liquid manure control practices as opposed to solid manure control practices are due to the higher (lower) probability of adoption for liquid (solid) manure control. Finally, a $1 per hour increase in the price of labor increases the probability of adopting solid manure control by 0.4% in average, but the confidence interval spans both negative and positive values. The seemingly peculiar positive sign might reflect a premium for skills or experience that translates into a greater appreciation of solid manure control benefits.

Contemporaneous Correlation and the Probability of Adopting Both Manure Control BMPs

The robustness of our results was ascertained by considering alternative specifications, allowing for interaction and quadratic terms and the possibility of contemporaneous correlation between the residuals of BMP equations. Several alternative specifications were considered, but they generated results that were quite similar to the ones reported in Tables 2A–E.[16] The same can be said about the multivariate probit estimation which can be loosely described as a seemingly unrelated probit regressions estimator. The multivariate probit model is estimated using the Geweke-Hajivassiliou-Keane (Borsch-Supan and Hajivassiliou, 1993; Geweke, 1991; Keane, 1994) smooth recursive conditioning simulator. The estimated correlation coefficients are reported in Table 3. The only correlation coefficient that is statistically different from zero is the one involving solid and liquid manure control practices (0.67). Therefore, we can conclude that the first three BMPs can be estimated as separate equations. As for the solid and liquid manure control practices, we need to ascertain whether accounting for contemporaneous correlation has much influence on the estimated coefficients.

To address this issue, we relied on a bivariate probit estimator to jointly reestimate these two equations. The results are reported in Table 4. The first two columns display the coefficients for the solid and liquid manure control equations, respectively. Comparing the results in Table 4 to the ones reported in Tables 2D and 2E, we can conclude that allowing for the error terms of the two manure control equations to be

[16] As discussed in the data section, the relevance of the telecommunication variable hinges on a positive correlation between the expenditure on telecommunication and information derived from telecommunication services. The results show that the estimated coefficients remain quantitatively and qualitatively robust when dropping the telecommunication variable.

Table 4. Bivariate Probit Estimation for Solid and Liquid Manure Management Practices

	(i)	(ii)	(iii)
	MANSOL	*MANLIQ*	
	$\hat{\beta}_i$	$\hat{\beta}_i$	Marginal Effects for Positive Outcomes $\Pr\begin{pmatrix} MANSOL = 1, \\ MANLIQ = 1 \end{pmatrix}$
	Mean	Mean	Mean
Producer Characteristics:			
AGE	0.0053 (0.0109)	−0.0064 (0.0091)	0.0007 (0.0018)
GENDER	1.0640[b] (0.4270)	0.9543[c] (0.4439)	0.3071[c] (0.1502)
EDUCATION	0.1936[d] (0.1055)	0.2033[b] (0.0871)	0.0348[c] (0.0172)
RESFARM	0.4637[e] (0.3543)	0.6781[b] (0.2845)	0.0685[c] (0.0332)
Farm Characteristics:			
PRODANIM	0.0010[a] (0.0003)	0.0015[a] (0.0005)	0.0003[a] (0.0001)
PRODCROP	−0.0812 (0.0852)	−0.0261 (0.0815)	−0.0134 (0.0141)
MACHINERY	0.0028[a] (0.0009)	0.0008 (0.0008)	0.0005[b] (0.0002)
BIOPROD	0.6033 (0.4936)	0.7029[e] (0.5313)	0.1525 (0.1496)
ENVCLUB	0.4497[d] (0.2389)	0.5318[a] (0.1762)	0.0768[c] (0.0339)
TELCOM	−0.1789[e] (0.1139)	−0.0123 (0.0464)	−0.0285[e] (0.0178)
Operational Variables:			
PLABOR	0.0203[e] (0.0124)	0.0030 (0.0116)	0.0033[e] (0.0021)
PFERT	0.0030 (0.0078)	0.0060 (0.0058)	0.0006 (0.0013)
Observations	269	269	
Log Likelihood (full model)	−230.9891		
rho(correlation *coefficient)*	0.6846 (0.1112)		
Predicted $\Pr\begin{pmatrix} MANSOL = 1, \\ MANLIQ = 1 \end{pmatrix}$			0.0991

Notes: Standard errors are in parentheses.
[a, b, c, d,] and [e] denote a two-tailed (one-tailed) significance level of 1% (0.5%), 2% (1%), 5% (2.5%), 10% (5%), and 20% (10%), respectively.

correlated does not impact much on the estimated coefficients. Notwithstanding small quantitative differences, our inferences remain qualitatively the same and there would be no point in presenting these results if it were not for the marginal effects on the probability of adopting *both* solid *and* liquid manure control practices reported in the third column of Table 4. These marginal effects are different from those reported previously because they pertain to the joint adoption of solid and liquid manure control practices. Being a female primary producer increases the probability of joint adoption by 30.7%. A higher educational degree and on-farm residence increase the probability of adopting both types of manure control practices by 3.5% and 6.9%, respectively. Revenue from animal production has also a significant effect at the 1% level. More specifically, the probability of jointly adopting the solid and liquid manure controls increases by 3% in response to a $100,000-increase in revenue from animal production. A $100,000-increase in the value of machinery leads to an increase in the probability of adoption by 5%. Although having more machinery facilitates the implementation of BMPs, having more capital might also free labor for BMP implementation. Still, as in

Tables 2D and 2E, these "size" effects, whereas positive, are nevertheless small. Belonging to an agro-environmental club raises the probability of joint adoption by 7.7%. None of the input price variables has a significant effect at the 10% level when conducting a two-tailed test.

Concluding Remarks

This study relies on a unique dataset collected in the Chaudière watershed in Quebec. The Chaudière watershed supports intensive agricultural activities, such as hog, dairy, and beef production. Water quality is a great concern and this is why the introduction of BMPs, such as crop rotation, surface runoff control, control of herbicide use, and solid and liquid manure control practices, is a public policy matter. This study focuses on the factors conditioning the adoption of BMPs. In this study, farm attributes, producer characteristics, and operational variables enter the specification of the BMP adoption model, which is rooted in random utility theory. We imposed inequality restrictions to incorporate priors motivated by economic theory and/or empirical regularity about the signs of individual coefficients. This can easily be implemented in a Bayesian estimation framework. We reported estimation results subjected to a "large" set of inequality constraints (Model 1), inequality constraints only on education and on-farm residence (Model 2), and inequality constraints to capture well-documented size effects (Model 3). Model 4 was unrestricted. This allows us to evaluate which inequality restrictions are more consistent with the data and assess the extent by which unrestricted coefficients are affected by the addition of prior information. We found high rejection rates for the large set of joint restrictions, but this was attributable to the same few variables across BMPs. In contrast, the inequality restrictions on education and on-farm residence and those on size effects were typically much more likely to hold than not. Therefore, our results are quite consistent with the literature and economic theory.

In accordance with our prior, higher education increases significantly the probability of adoption of most BMPs. Women and producers residing on farm grounds are more likely to adopt solid and liquid manure control practices. Older producers are more likely to implement crop rotation and riparian buffer strips. Even though older producers have shorter planning horizons than their younger counterparts, their lower debt-equity ratio makes it easier for them to financially support the costs of implementing BMPs. Farm size evaluated in terms of crop and animal production impacts on the probability of BMP adoption. The bigger the crop production, the more likely it is that crop rotation, riparian buffer strips, and herbicide control practices will be implemented. Farms with larger scale of animal production have a higher probability of implementing crop rotation, riparian buffer strips, and solid and liquid manure control practices. Farms with more machinery are more likely to adopt BMPs given that machinery saves time and correlates with wealth. Because many smaller producers need off-farm income to support their household expenditures, it is not surprising that they are facing more binding financial and time constraints. Belonging to an agro-environmental club increases the likelihood of adoption of most BMPs. Also, having a biological/organic production certificate increases the likelihood of adopting solid and liquid manure control practices. Except for the price of labor, which has a respectively negative and positive impact on the probability of adopting crop rotation and solid manure control practices, the price of inputs did not have an incidence on BMP adoption. Although it is expected that lower prices paid for inputs reflect good operational practices and facilitate adoption of BMPs by relaxing financial constraints, the positive effect of higher per unit labor costs might reflect a premium for skills or experience that facilitates adoption.

We tested for the presence of contemporaneous correlation by estimating a multivariate probit and we found evidence of correlation only between the residuals of the solid and liquid manure control equations. This legitimized our single-equation results for the riparian buffer, herbicide control, and crop rotation BMPs. For the two manure control

BMPs, the estimation of a bivariate probit model yielded coefficients that were very close to the ones that had been estimated equation by equation. Thus, the results presented for solid and liquid manure control measures are robust.

In terms of provincial and federal policies, it is important to note that the farms that produce the most runoffs are the large ones and to the extent that large crop and large animal producers are more likely to adopt BMPs than smaller producers, it needs not to be that important to achieve very high adoption rates. However, Beaulieu (2001) found out that most small farms are primarily located in high-density livestock areas in Quebec and Ontario where water quality is at risk for falling below acceptable thresholds. Then, monetary incentives might be needed to encourage the adoption of BMPs. Our results indicate that agro-environmental clubs transfer useful information about agro-environmental issues and practices to producers that ultimately influence BMP adoption. However, the effect of environmental clubs on BMP adoption varies across BMPs (with probability increases ranging from 0 to 21%) and this suggests that environmental clubs could probably be even more effective by reconsidering their strategies to boost the adoption of certain BMPs. Nevertheless, we feel that the government's financial assistance to these clubs is money well-spent.

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