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THE GROWTH IN ORGANIC AGRICULTURE: TEMPORARY SHIFT OR STRUCTURAL CHANGE?

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Short paper presented at 2004 AAEA Annual Meeting, Denver 1-4 august 2004

Abstract

This paper investigates the growth in the number of organic producers in the Netherlands. Using Bayesian techniques a logistic growth model explaining the share of organic farms is estimated. Prior information is used to estimate and compare three different models on the future of organic farming.

1. Introduction¹

In most European countries the organic farming sector has grown rapidly in recent years. For example, in the Netherlands the number of organic farmers increased from 439 in 1991 (0.36% of total number of farmers) to 1088 in 2002 (1.21% of total). A potential explanation for this increased interest of farmers in organic farming is the sequence of crises in agriculture (classical swine fever, BSE, FMD). Because of these crises some farmers may have concluded that the conventional way of farming is not sustainable inducing them to shift to organic production. Other potential explanations are public opinion signals, expected increase in market demand for organic products, premium prices for organic products, income support during the transition period, investment subsidies, tax benefits or the increased environmental legislation that reduced the difference between conventional and organic farming systems. The Dutch Ministry of Agriculture has even set a policy target for the number of organic farmers in 2010. By that time 10% of the Dutch farmers should farm organically.

An important question, however, is how this growth will evolve in the future. Is organic farming really becoming an important factor in the agricultural sector as some European policy makers would like to see it, or is the recent interest in organic practices just temporary? Different views have been expressed on this question. Lampkin for example (1999), suggests that the total share of organic farming could become 10% to 30% in 2010 for Europe as a whole. The Dutch government also aims at a 10% share of organic farming in 2010. A second view is more radical. The current growth in organic farming has led to a widespread acceptance of organic production among producers and consumers. This reinforces the growth of the organic sector even more and eventually all farmers will produce organically. This scenario is motivated by the increase in knowledge about organic production practices and problems encountered, stimulating even more

¹ Computations reported in this paper were undertaken (in part) using the Bayesian Analysis, Computation and Communication software (<u>http://www.econ.umn.edu/~bacc</u>) described in Geweke (1999).

farmers to switch. Moreover, conventional farmers start using elements from organic production, reducing the differences between conventional and pure organic production. A third view is the opposite. Although there has been some growth in the number of organic farmers recently, this growth has levelled off already. The current share is already close to a stable level of about 1.5% at most. The growth in organic farming was a strong reaction to a number of crises in agriculture but interest is already diminishing. Increasing labor and land prices give organic farming cost disadvantages so that it will not be viable in the future.

The objective of this paper is to analyze the observed growth in the share of organic agriculture in the Netherlands and to investigate how this growth relates to the three views on the future of organic farming mentioned above. The evolution of the share of organic farming is assumed to follow a pattern conforming to the well-known S-curve of innovation (Padel, 2001). The first farmers that adopt organic practices are typical innovators, followed by the early adopters, the majority and finally the laggards. The three views mentioned can all be modeled using this framework, with differences in growth rates and saturation levels.

The S-curve for the development of the share of organic farming is estimated using Bayesian methods and modern sampling techniques. The advantage of using the Bayesian approach is that the use of prior information improves the estimation results given the limited amount of data available. Moreover, the three different hypotheses on the future development of organic farming allow for three different sets of prior information that can be interpreted as different expert views. Bayesian model selection techniques are used to select the model (hypothesis) that conforms most with the data. This is an advantage over classical approaches where it may not be possible to test different hypotheses against each other.

The contributions of this paper are twofold. First, different hypotheses on the future of organic

farming are investigated and tested providing an empirical foundation for the future of the organic sector. This analysis is relevant for farmers that find it difficult to judge the current growth in organic farming when considering viable alternatives for their farms. Moreover, policy makers may use the results to evaluate or adapt current policies that stimulate switching to organic farming according to their policy goals (e.g. specific share of organic agriculture). The methodological contribution of this paper is to empirically estimate S-curves of innovation combining observed data on structural change in the agricultural sector with different hypotheses on future developments in one coherent Bayesian framework.

The paper is built up as follows. Section two gives a quick overview of the recent growth in the share of organic farming in the Netherlands. Section three presents the methodology used in this paper. The use of S-curves in analyzing diffusion of innovations and the Bayesian approach used to estimate the S-curve are discussed. Attention is given to the specification of priors and the procedure for model selection. In section four results and test outcomes are presented and section five ends with conclusions and policy implications.

2. The development of the organic sector in the Netherlands

Compared to other European countries the share of organic farming in the total agricultural sector of the Netherlands is still rather modest. Austria for example already has a share of 9% of organic farmers. Also big agricultural producers like Germany (3.31%) and Denmark (6.4%) have a higher share of organic producers. However, a common observation in all European countries is that the share of organic farming increased rapidly in recent years. Table 1 gives an overview of the total number of farms, the number of organic farms and the share of organic in the Netherlands in the period 1986-2002.

Year	All farms	Organic farms	Percent. organic	Change in percent.
1986	133566	278	0.208 %	-
1987	131708	305	0.232 %	0.023
1988	129421	332	0.257 %	0.025
1989	127008	359	0.283 %	0.026
1990	124504	399	0.320 %	0.038
1991	122167	439	0.359 %	0.039
1992	120472	464	0.385 %	0.026
1993	119234	490	0.411 %	0.026
1994	115679	505	0.437 %	0.026
1995	112681	521	0.462 %	0.025
1996	110113	554	0.503 %	0.041
1997	107340	579	0.539 %	0.036
1998	104168	705	0.677 %	0.138
1999	100759	786	0.780 %	0.103
2000	96577	906	0.938 %	0.158
2001	91759	1024	1.116 %	0.178
2002	88492	1088	1.229 %	0.113

Table 1.Development of organic farming in the Netherlands

Source: Statistics Netherlands (various years).

From table 1 a number of things can be learned. First, it is clear that the share of organic farms is still rather small. Although there is a lot of attention paid to it only a little more than 1% of the total number of farms is organic. Second, the growth in the share of organic can be explained by two factors: the rapid decrease in the number of all farms from 133566 in 1986 to 88492 in 2002 and the increase in the number of organic farms from 278 to 1088 in the same time span. Had the overall number of farms remained constant then the share of organic farms is not constant. Up to 1997 the average number of new organic farms was about 27. Growth was notably strong between 1997-2001 with on average each year about 111 new organic farms. However, in 2002 only 64 farms started using organic practices. The same observation can be made on the change in the percentage. Modest but steady growth until 1996 and a much more rapid increase in the share between 1997-2001. The year 2002 had a lower change in the percentage. So, is the growth already leveling off or is this just a temporary downswing?

3. Methodology

In section two it is observed that the growth in the share of organic farming started rather modest but increased in the late 1990's. This observation corresponds with the early phase in the wellknown S-curve for diffusion of technological change. Diffusion S-curves have a long history in economic analysis (see e.g. Griliches, 1957). The assumption that diffusion follows an S-like pattern is based on discerning different groups of adopters. The first to adopt are typical innovators. The technology is new, not well-known and there is not much experience. Innovators are willing to spend time on learning it and take some risks. This corresponds with the initial flat part of the Scurve. The nexts to adopt are the so-called early adopters. Here the technology becomes accepted and the S-curve becomes more steep. When the majority adopts growth is at its fastest rate. Finally the laggards adopt, corresponding with the upper flat part of the S-curve.

The mathematical model for an S-curve is the logistic specification:

$$sh_t = \frac{c}{1 + e^{a - bt}} \tag{1}$$

The share of organic farms (sh_t) evolves over time (t) depending upon the values of the (positive) parameters *a*, *b* and *c*. Parameter *c* is the maximum value (ceiling) the share can attain, whereas *b* determines the speed of growth (rate of adoption). With respect to the different views considered in this study parameter *c* plays an important role since it sets the maximum share organic farming is believed to attain.

There are a number of options available to estimate equation (1). One could estimate the nonlinear expression directly using a suitable non-linear estimation technique (e.g. NLS, ML or GMM). An alternative is to linearize the equation and regress the logarithm of the log-odds ratio on time using standard estimation techniques (see e.g. Griliches, 1957). However, this is only possible if the parameter c is fixed and known. An alternative is to estimate the corresponding differential equation (e.g. Oliver, 1964). It can be shown that equation (1) is the solution to the following differential equation:

$$\frac{\partial sh}{\partial t} = b \cdot sh - \frac{b}{c} \cdot sh^2 \tag{2}$$

By estimating the discrete-time version of this differential equation the essential parameters *b* and *c* can be obtained.

Bayesian approach

Using classical estimation techniques to estimate the parameters of the logistic specification in this study has a number of drawbacks. First, the amount of data is rather limited (only 16 observations) and therefore large sample properties required for consistency are not fulfilled. Second, the parameters *b* and *c* are defined as positive, something which is not guaranteed using classical methods². Third, in the classical estimation approach it is possible to test hypotheses on parameters (e.g. H_0 : $\hat{c} = 0.1$) but this is done case by case. So, in principle all the formulated hypothesis on the development of organic farming may be rejected (or none is rejected), leaving us indecisive on what model is most likely to prevail. This all-or-nothing approach of hypotheses testing does not sharpen our beliefs about which model is most likely to prevail (Greene, 1997:320).

In this study Bayesian estimation techniques are used to estimate the parameters of the logistic diffusion model. See Geweke (2003) or Koop (2003) for a thorough discussion on Bayesian econometrics. The advantage of the Bayesian approach is that the different views on the future of organic farming can be formulated as prior information to be used in estimation. The different

views imply particular prior values for c. Moreover, we can incorporate our knowledge (belief) on the positive nature of both b and c. Posterior probabilities of the parameters are obtained using Bayes rule:

$$p(\theta^{i} | y, M_{i}) = \frac{p(y | \theta^{i}, M_{i})p(\theta^{i} | M_{i})}{p(y | M_{i})}$$

$$(3)$$

where $p(\theta^{i} | M_{i})$ is the prior probability of the parameters θ^{i} in model M_{i} , $p(y | \theta^{i}, M_{i})$ is the likelihood of the data *y* conditional upon parameters θ^{i} and model M_{i} , $p(y | M_{i})$ is the marginal likelihood and $p(\theta^{i} | y, M_{i})$ is the posterior parameter probability. Parameter priors and model specifications are explicitly expressed in the Bayesian setup. Obtaining posterior probabilities requires integrating over the distributions of the prior and the likelihood. Whereas in the past only an (analytical) solution was possible if appropriate (conjugate) prior distributions were used, nowadays posterior probability distributions can be obtained using simulation techniques (e.g. Gibbs sampler). For this study the software package BACC for Matlab is used. BACC can perform posterior simulation using a number of distributions. Specifying prior values (mean and precision parameters) and details on the posterior simulation procedure enables to estimate a number of well-known models (e.g. normal linear regression model, SUR, censored linear models). See McCausland and Stevens (2003) for details. A drawback of BACC is that it doesn't allow for estimation of non-linear models like equation (1). Therefore, the corresponding differential equation (2) is estimated here.

If we attach equal prior weights to the different views expressed on the future of organic farming, the three models can be compared using the Bayes factor, $BF_{ij} = p(y | M_i)/p(y | M_j)$,

² OLS on equation (2) indeed resulted in a negative parameter value for c.

which is the ratio of the marginal likelihoods of models *i* and *j*. If we attach a priori different weights to the different views the Bayes factor can be multiplied by the prior odds ratio $p(M_i)/p(M_i)$ resulting in the posterior odds ratio.

Specification of priors

In this paper three models of interest are specified plus a realistic benchmark model. Model A corresponds with the Dutch government objective of a 10% share of organic farms by 2010, so the mean prior \underline{c} is set to 0.1. Model B is called the optimistic model with mean prior $\underline{c} = 1$. Model C is the pessimistic model with prior $\underline{c} = 0.015$. The benchmark model D is based upon a forecast of the non-linear model (1) estimated with NLS, giving a mean prior of 0.03. Since our main interest is in comparing models with respect to parameter c, the prior specification for b is the same for all models. A mean prior \underline{b} of 0.24 is specified based on the value that is necessary to go from 0 to c in about 25 years (period 1986-2010). Besides the mean values, the precision \underline{h} of the priors is also important. It reflects how strong our beliefs are on the prior means. Precision \underline{h}_b is set at 70, which corresponds with a 95% normal confidence interval [0; 0.48]. Note that this implies that b is bound to be positive. Since we basically estimate b and the construct b/c, which would require a quotient of precision parameters, we use the same precision parameter for the latter construct.

4. Results

All four models were estimated using BACC simulation for the Normal Linear Model. This applies a Gibbs sampling procedure for the posterior distribution of the parameters. 10000 samples were drawn for the posterior distribution. Estimation results are given in table 2:

Table 2.	Parameter estimates for four different models for organic farming					
	Model A	Model B	Model C	Model D		
ĥ	0.157	0.149	0.209	0.178		
ĉ	0.065	0.591	0.013	0.022		

Note that the estimates for the rate of adoption parameter b are all lower than the mean prior we specified. So, our prior beliefs on this parameter were too high and have been updated by the data. The estimates for the ceiling parameter *c* are all lower than the prior ceilings we specified. This may be due to the approximation inherent in any estimation procedure, but also because the actual ceiling corresponding with the data and brought into the estimation procedure via the likelihood is different from the mean priors we specified.

The main objective in this paper was to compare the probabilities of the different models specified based on different beliefs in the society on the future of organic farming. Given the estimated the models where prior beliefs are updated by the information in the data it is therefore interesting to compare the Bayes factors corresponding to the different models. These are given in table 3:

Table 3.	e 3. Bayes factors for different models					
\	Model <i>i</i>	Model A	Model B	Model C		
Model j						
Model A		1	0.968	0.914		
Model B		1.033	1	0.945		
Model C		1.094	1.058	1		
Model D		0.977	0.946	0.893		

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A Bayes factor larger than 1 indicates that model *i* has a higher probability than the comparison model. It is interesting to see that none of the models relflecting a particular view on the future farming (government 10% share (A), optimistic 100% share (B) or pessimistic 1.5% share (C)) has a higher probability than the comparison model D based on the NLS forecast. Of course, this is not surprising given that model D has the highest likelihood. Compared to this model D, the government 10% model has the highest Bayes factor of 0.977, indicating that the probability of this model is not that different from the 'forecast' model D. Surprisingly the pessimistic model of a stagnating growth of organic farming has a lower Bayes factor than the optimistic 100% model. Apparently the recent rapid growth in the share of organic farms is more in line with large acceptance than stagnation of the growth. Considering the hypothetical models it is concluded that Model A has a slightly higher probability than models B and C. B in turn has a slightly higher probability than model C.

5. Discussion and conclusions

This paper uses a Bayesian approach to estimate logistic growth models for the development of the share of organic farms in the total number of farms. Three models are based on three views expressed on the future of organic farming, i.e. a share of 10% in 2010, a complete transition to organic farming and stagnating growth in the share of organic farms, implying different prior values that are used in estimation. The models are compared on the basis of Bayes factors. It turns out that the government view of 10% is most likely compared to the other two hypotheses. This model also has a probability close to a benchmark model based on NLS regression of the logistic function. Overall, the Bayes factors are not very distinctive implying that all scenario's for the development of organic farming are more or less just as likely. There is no model that strongly dominated the others.

This first version of the paper can be extended in a number of ways. First, in stead of estimating the differential equation corresponding to the logistic growth process, the non-linear logistic specification could be estimated using Bayesian techniques. Furthermore, other functional forms for the growth in the share of organic farming could be considered. All models considered here assume

the logistic S-curve specification. Finally, some attention should be paid to defining credible sets for the individual parameters and to prediction with these models.

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