# Evaluating Different Growth Scenarios for Organic Farming Using Bayesian Techniques

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# Evaluating Different Growth Scenarios for Organic Farming Using Bayesian Techniques

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*Abstract* - **Different views exist on the future development of organic agriculture. The Dutch government believes that in 2010 10% of the farm land will be used for organic farming. Others have a more radical view: due to increasing emphasis on sustainable production in the end all farming will be organic. Others believe in a more pessimistic scenario in which the recent growth in organic was just a temporary upswing and that the share of organic farmers already reached its maximum. In this paper different potential scenarios for the further growth of organic farming are evaluated using Bayesian techniques. A nonlinear logistic growth model explaining the share of organic farms is estimated using available historical data for Dutch agriculture. Various scenarios imply different prior values for the parameters. Because of the non-linear model specification a Metropolis-Hastings algorithm is used to simulate the posterior densities of the model parameters. Finally, using Bayesian model comparison techniques probabilities can be attached to the different scenarios. The proposed methodology is a promising tool for analysing technology diffusion in general when different scenarios for diffusion are possible and limited data is available.**

*Keywords* - **Organic farming, Bayesian analysis, non-linear logistic growth curves**

## I. INTRODUCTION

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 1274 in 2006 (1.6% 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, increased 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.

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, or is the recent interest in organic practices just temporary? Different scenarios for the share of organic farming are possible and some of these scenarios also have been expressed by some experts. Lampkin [1] for example, 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 potential scenario 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 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 and more pessimistic. 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 2.5% at most. The growth in organic farming was a strong reaction to a number of crises in agriculture but interest is already diminishing. Increasing labour 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 realized growth in the share of organic agriculture in the Netherlands and to investigate how this growth relates to the three scenarios 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 logistic growth curve (“S-curve”) of innovation [2]. 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 modelled using this framework, with differences in growth rates and saturation levels.

The nonlinear logistic growth model explaining the share of organic farms is estimated using available historical data for Dutch agriculture and Bayesian econometric methods. Because of the non-linearity of the model a Metropolis-Hastings algorithm is used to simulate the posterior densities of the model parameters. The advantage of using the Bayesian approach is that prior information on the parameters can be combined with the available data in order to improve the estimation results. The three different scenarios on the future development of organic farming imply three different sets of prior information that can be interpreted as different expert views. Bayesian model comparison techniques are used to attach probabilities to the different scenarios. This is an advantage over classical estimation approaches where it is not possible to compare more than two models with each other.

The contributions of this paper are threefold. First, different scenarios on the future of organic farming are investigated and compared in an explicit empirical framework providing an quantitative insight in 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 second contribution is the exposition of how to estimate non-linear S-curves of innovation using observed data and prior information based on different scenarios or expert knowledge. This is relevant since in modern society many new technologies are introduced that may require quantitative analysis. Examples in agriculture are the introduction of GM crops and milking robots. The methods used here also allow for attaching probabilities to different scenarios or views expressed by experts or stakeholders on the future development of certain technologies. Logistic growth curves are also a popular tool in evolutionary economics [3] and therefore the methodology presented here may also contribute to empirical analyses in this area. A third contribution is that it is explained how non-linear regression models in general can be estimated using Bayesian techniques. This is relevant for researchers who for example estimate non-linear production or growth functions using prior information on elasticities or growth rates.

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.

## II. 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.

From table 1 a number of things can be concluded. First, it is clear that the share of organic farms in the Netherlands 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 133844 in 1986 to 79435 in 2006 and the increase in the number of organic farms from 278 to 1274 in the same time span. Had the overall number of farms remained constant then the share of organic would only be 0.95%. A third lesson from this table is that the growth in the number 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 2004 only 16 farms started using organic practices, followed by 31 new starters in 2005 and 42 in 2006. 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. In 2004 the change in percentage dropped to 0.046, but rising again in the years 2005 and 2006. So, is the growth indeed levelling off the last couple of years or is this just a temporary downswing?

Table 1 Development of organic farming in the Netherlands

| Year | All farms | Organic farms | Percent. organic | Difference in percentage |
|---|---|---|---|---|
| 1986 | 133844 | 278 | 0.208% | - |
| 1991 | 122606 | 439 | 0.358% | 0.039% |
| 1996 | 110667 | 554 | 0.501% | 0.040% |
| 1997 | 107919 | 579 | 0.537% | 0.036% |
| 1998 | 104873 | 705 | 0.672% | 0.136% |
| 1999 | 101545 | 786 | 0.774% | 0.102% |
| 2000 | 97483 | 906 | 0.929% | 0.155% |
| 2001 | 92783 | 1024 | 1.104% | 0.174% |
| 2002 | 89580 | 1088 | 1.215% | 0.111% |
| 2003 | 85501 | 1185 | 1.386% | 0.171% |
| 2004 | 83885 | 1201 | 1.432% | 0.046% |
| 2005 | 81830 | 1232 | 1.506% | 0.074% |
| 2006 | 79435 | 1274 | 1.604% | 0.098% |

Source: [4].

## III. METHODOLOGY

### *A. Logistic growth curves for organic farming*

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 well-known S-curve for diffusion of technological change. Diffusion S-curves have a long history in economic analysis (see e.g. [5]). 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 S-curve. The next ones 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. In this paper it is assumed that the share of organic farming follows a S-curve pattern.

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

$$share_t = \frac{\alpha}{1+e^{-\beta(t-\gamma)}} \tag{1}$$

The share of organic farms ($share_t$) evolves over time ($t$) depending upon the values of the (positive) parameters $\alpha$, $\beta$ and $\gamma$. Parameter $\alpha$ is the maximum value (ceiling) the share can attain. With respect to the different scenarios considered in this study parameter $\alpha$ plays an important role since it sets the maximum share organic farming is believed to attain. Parameter $\beta$ determines the speed of growth (rate of adoption), and $\gamma$ is a scaling parameter. The advantage of this standard logistic specification is that it is simple and that its parameters have a straightforward interpretation. A disadvantage is that the resulting S-curve is symmetric round the inflection point $\alpha/2$. This disadvantage led Bewley and Fiebig [6] o specifying a flexible logistic growth model that is not necessarily symmetric and has a variable inflection point. However, in their empirical comparison of various logistic growth specifications, Meade and Islam [7] found that the standard logistic growth specification outperformed this flexible specification.

There are a number of options available to estimate the non-linear equation (1). A classic approach is to linearise the equation and regress the logarithm of the log-odds ratio on time using standard estimation techniques (see e.g.[5]). However, this is only possible if the parameter $\alpha$ is fixed and known. An alternative is to estimate the corresponding differential equation [8]. It can be shown that equation (1) is the solution to the differential equation:

$$\frac{\partial share}{\partial t} = \beta \cdot share - \frac{\beta}{\alpha} \cdot share^2 \tag{2}$$

By estimating the discrete-time version of this differential equation the essential parameters $\alpha$ and $\beta$ can be obtained. However, this indirect approach does not allow for estimating the scaling parameter $\gamma$ so it is less flexible. Moreover, proper estimation of $\alpha$ and $\beta$ requires imposition of a parameter restriction in the model, basically leaving the model non-linear in parameters. A third option is to estimate the non-linear model directly using a non-linear estimation technique (e.g. Nonlinear Least Squares (NLS), Maximum Likelihood (ML) or Generalised Method of Moments (GMM)). However, using classical estimation techniques (NLS, ML or GMM) to estimate the parameters of the logistic specification (1) has a number of drawbacks in general and some in particular for this study. First, the parameters $\alpha$ and $\beta$ are positive by definition, something that is not guaranteed using classical econometric methods[1]. Second, using classical estimation approaches it is possible to test specific hypotheses on parameters (e.g. $H_0 : \hat{\alpha} = 0.1$ or $H_0 : \hat{\alpha} = 1$) but if a specific null hypothesis is rejected the alternative hypothesis ($H_1$) is not very informative. In principle all the formulated scenarios on the development of organic farming could be rejected, or the opposite, none of them gets 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 [9]. Third, the amount of data used in this study is limited (only 21 observations) and therefore large sample properties required for consistency are not fulfilled.

*B. Bayesian estimation of non-linear models*

Because of the drawbacks of classic estimation techniques, a Bayesian non-linear estimation technique is used in this paper. See [10] or [11] for a thorough discussion on Bayesian econometrics. With Bayesian techniques, prior information on the parameters (e.g. positiveness) can be included in the estimation procedure. Prior information is also useful in applications with limited data available such is the case in this study. In this study the prior information on parameters is based on the different scenarios for the future of organic farming that were discussed in the introduction. These different scenarios imply specific prior distributions for $\alpha$, the assumed ceiling of the share of organic. For the 10% scenario we assume $\underline{\alpha}_1 \sim N(0.1, 0.01^2)$ as prior distribution for $\alpha$ [2]. The choice of 0.01 for the standard deviation implies that we assume that 95% of the probability mass is between 0.8 and 0.12 (66% is between 0.9 and 1.1). For the full transition (100%) scenario it is assumed that $\underline{\alpha}_2 \sim N(0.975, 0.01^2)$ and for the pessimistic (2.5%) scenario $\underline{\alpha}_3 \sim N(0.025, 0.0025^2)$, so that here 95% of the probability mass between 0.002 and 0.003. A realistic prior distribution for $\beta$ can be derived by dividing both sides of the differential equation (2) by *share*, so that $\beta$ can be inferred from observed growth rates and different values for $\alpha$. This gives a prior distribution $\underline{\beta} \sim N(0.4, 0.2^2)$. Finally, based on observed shares of organic and the range of specified priors for $\alpha$ and $\beta$, a reasonable prior for $\gamma$ is $\underline{\gamma} \sim N(20, 6^2)$. Note that for the different scenarios we keep the priors for $\beta$ and $\gamma$ the same. Besides prior distributions on the three parameters we also need to specify a prior distribution on the error precision $h$ [3]. The specified error precision reflects our belief in the strength of the prior distributions for the three parameters and is, in line with the literature specified as a gamma distribution, i.e. $\underline{h} \sim G\ (1000,1)$. The mean value of 1000 in the gamma prior implies an expected error variance of 0.001, or an error standard deviation of 0.0316, which seems reasonable in this application since observed shares of organic do not vary much and are all between 0.002 and 0.016.

Posterior probability distributions of the model parameters are obtained using Bayes rule:

$$p\left(\theta^i \mid y, M_i\right) = \frac{p\left(y \mid \theta^i, M_i\right) p\left(\theta^i \mid M_i\right)}{p\left(y \mid M_i\right)} \tag{3}$$

where $M_i$ denotes one of the three different models that we consider based on the three scenarios, $p\left(\theta^i \mid M_i\right)$ denotes the prior distributions of the parameters $\theta^i$ in model $M_i$, $p\left(y \mid \theta^i, M_i\right)$ is the likelihood of the data $y$ conditional upon parameters $\theta^i$ and model $M_i$, $p\left(y \mid M_i\right)$ is the marginal likelihood and $p\left(\theta^i \mid y, M_i\right)$ is the posterior parameter probability.

Summarizing the expression for the non-linear logistic growth curve as $f(t,\theta)$ and assuming that the residuals are normally distributed, i.e. $\varepsilon \sim N\left(0_N, h^{-1} I_N\right)$, allows writing the likelihood function:

$$p\left(y \mid \theta^i, M_i\right) = \frac{h^{\frac{N}{2}}}{(2\pi)^{\frac{N}{2}}} \left\{ \exp\left[ -\frac{h}{2} \left(y - f(t,\theta)\right)' \left(y - f(t,\theta)\right) \right] \right\} \tag{4}$$

The resulting posterior density is proportional to the prior times the likelihood:

[1] This problem also appeared when equation (2) initially was estimated using OLS, resulting in a negative parameter estimate for $\alpha$.

[2] Note that priors are indicated by a lower bar ($\underline{\alpha}$) and posteriors by an upper bar ($\overline{\alpha}$).

[3] The error precision $h$ is the inverse of the more commonly know error variance, i.e. $h=1/\sigma^2$.

$$p(\theta,h \mid y) \propto p(\theta,h)\frac{h^{\frac{N}{2}}}{(2\pi)^{\frac{N}{2}}}\cdot \left\{\exp\left[-\frac{h}{2}(y-f(t,\theta))'(y-f(t,\theta))\right]\right\} \quad (5)$$

Note that there is no analytical solution to this expression and therefore the posterior parameter distributions can only be obtained using posterior simulation techniques. Due to the non-linearity of the logistic growth function $f(t,\theta)$ we use a Random Walk Chain Metropolis-Hastings algorithm [11], to simulate the posterior density.

After obtaining the posterior parameter densities we can interpret the parameters and compare the models based on different prior distributions related to the three scenarios. Attaching equal prior weights to the different scenarios on the future of organic farming, the three models can be compared using the Bayes factor, $BF_{ij} = p(y \mid M_i)/p(y \mid M_j)$, which is the ratio of the marginal likelihoods of models $i$ and $j$[4]. The Bayes factor indicates how likely one model is compared to another, thus providing a direct and clear way of comparing different models and showing how Bayesian techniques solve the criticism on the all-or-nothing hypothesis testing approach in classical econometrics that was discussed above.

The only data used in estimation are the observed shares of organic farming in the period 1986-2006, given in the fourth column of table 1, yielding a small dataset of 21 observations.

## IV. RESULTS

The posterior simulators were programmed in Matlab. To simulate the posterior densities, 27500 draws were taken, from which 2500 initial (‘burn-in’) draws were deleted. Besides the three models based on the three scenarios, a fourth model with prior densities based on ML estimation was estimated for comparison. Posterior means of parameters for these four models are given in table 2.

Table 2 Posterior means (standard deviations in parentheses) for four different models

| | 10% scenario | Full transition | Pessimistic 2.5% | ML model |
|---|---|---|---|---|
| $\bar{\alpha}$ | 0.098<br>(0.010) | 0.974<br>(0.010) | 0.025<br>(0.0025) | 0.046<br>(0.017) |
| $\bar{\beta}$ | 0.225<br>(0.086) | 0.385<br>(0.119) | 0.261<br>(0.123) | 0.135<br>(0.017) |
| $\bar{\gamma}$ | 27.711<br>(2.860) | 31.729<br>(3.245) | 17.962<br>(2.557) | 25.030<br>(4.199) |
| $\bar{h}$ | 18497<br>(6072) | 14580<br>(4888) | 19681<br>(6159) | 20595<br>(6376) |

The posterior densities for $\alpha$ for the three different scenario’s are all more or less similar to the specified prior densities, indicating that the priors had much influence in estimating these parameters. This influence could be lessened by specifying larger standard deviations in the prior densities. However, as motivated in section 3 the specified standard deviations were based on the three scenarios considered and are also limited by the limited range of values $\alpha$ can take. Moreover, the Bayesian approach was, among other reasons, also motivated by the fact that only 21 observations are available. An explanation for the strong impact of these prior values is also the fact that the share of organic farming is still growing and that the saturation rate (ceiling for $\alpha$) is still far from being reached so that this parameter is hard to infer from the data. It is also interesting to observe that the ML based model estimates a maximum share of 4.6% for organic farming.

The parameter estimates for $\beta$ and $\gamma$ are less affected by the specified prior distributions, although it should be noted that the specified standard deviations were also larger for both parameters. Not surprisingly the rate of growth parameter $\beta$ was largest for the full transition (100%) scenario, i.e. 0.385. Posterior means for $\beta$ for the three scenarios were all higher than the ML estimate. Finally, the estimated error precision was higher in all cases than then specified prior value, indicating that the prior choice was rather conservative here. Figure 1 shows the different estimated logistic growth curves for the time period 1986-2006.

[4] Note that if different weights are given to the priors, in case we believe certain scenarios to be less likely than other, the Bayes factor can be multiplied by the prior odds ratio, resulting in the posterior odds ratio that can also be used for model comparison.

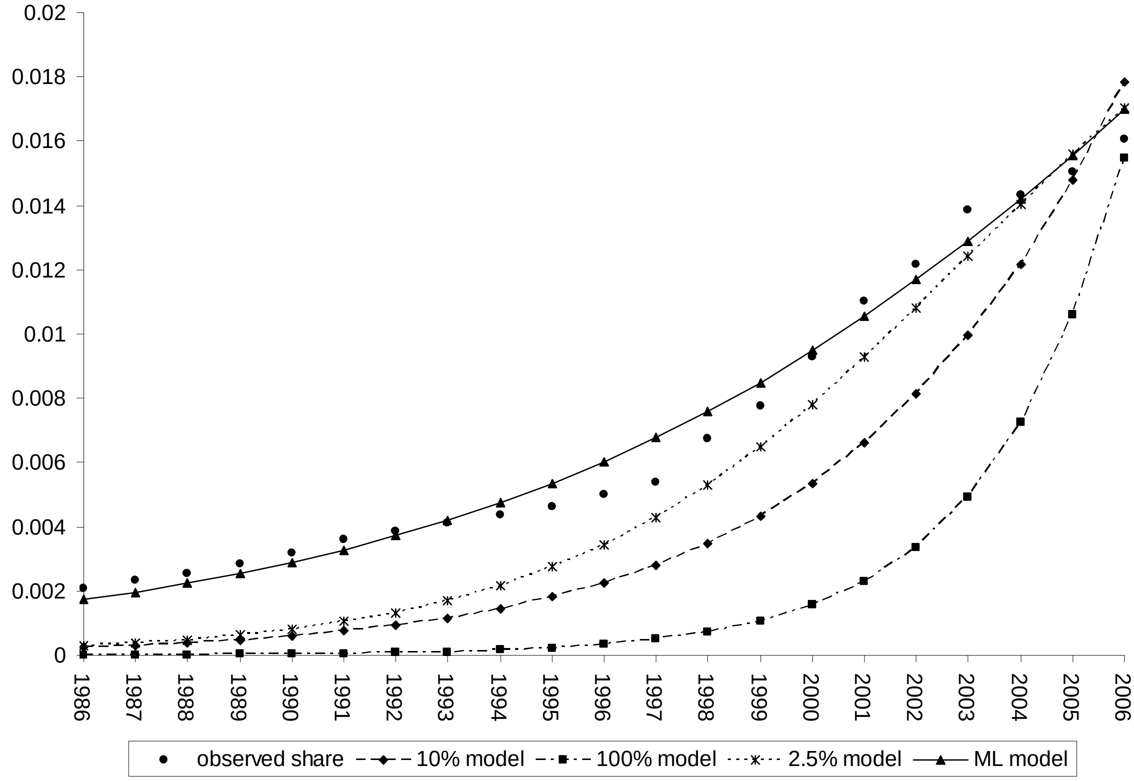


Fig. 1 Estimated logistic growth curved for the share of organic farming, 1986-2006

The main objective of this paper was to compare the probabilities of different models based on different scenarios for the future of organic farming. Given the estimated 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 Bayes factors for different scenario's (P(scenario i)/P(scenario j))

| *i* / *j* | 10% scenario | Full transition | Pessimistic 2.5% | ML model |
|---|---|---|---|---|
| 10% scenario | - | 0.033 | 9.846 | 22.949 |
| Full transition | 30.078 | - | 296.156 | 690.274 |
| Pessimistic 2.5% | 0.102 | 0.003 | - | 2.331 |
| ML model | 0.044 | 0.001 | 0.429 | - |

A Bayes factor larger than 1 indicates that model *i* has a higher probability than the comparison model. None of the models reflecting a particular scenario on the future farming (10% scenario, full transition (100%) scenario or pessimistic 2.5% scenario) has a higher probability than the model with priors based ML estimates. In other words, a final share of 4.6% is about 23 times more likely than a share of 10% and 690 times more likely than a full transition scenario. The pessimistic scenario of only 2.5% does better in this comparison being only half as likely as the outcome of the ML model. Of the three potential scenarios considered in this analysis the pessimistic scenario 2.5% dominates the other two scenarios. It is about 10 times as likely as the 10% scenario and nearly 300 times as likely as a scenario of full transition.

## V. DISCUSSION AND CONCLUSIONS

This paper uses a Bayesian approach to estimate nonlinear logistic growth models to analyse the growth in the share of organic farms in the total number of farms. Three models based on three potential scenarios for the future of organic farming, implying different prior distributions, were estimated and compared on the basis of Bayes factors. The three scenarios considered are a final share of 10%, which corresponds by the target set by the Dutch government, a complete transition to organic farming and a scenario of stagnating growth in the share of organic resulting in a final share of only 2.5%. The results indicate that this last pessimistic scenario is the most likely of the three, given the development of the share from 1986 to 2006. However, all three scenario-based models are less likely than a benchmark model based on non-linear ML estimation of the logistic growth function. This ML based model predicted a final share of 4.6% for organic farming in the Netherlands.

The methods used in this paper have interesting potential for further use. First, combining prior information based on plausible ranges of parameters may help in estimating logistic growth functions that are often used in studies assessing technology diffusion when only a limited amount of data is available. With limited data, such assessments are often based or complemented by 'expert' views or scenario analyses. The methodology used in this paper allows for attaching probabilities to such expert views or scenarios, based on the available data. In this way it is possible to assess the plausibility of these expert views or scenarios.

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