Presented at:
The Agricultural Economics Society's 81st Annual Conference, University of Reading, UK
2nd to 4th April 2007

Bayes Estimates of Time to Organic Certification:

Caroline Hattam* and Garth Holloway**

*Scottish Agricultural College, Kings Buildings, Edinburgh, Scotland, caroline.hattam@sac.ac.uk;
**Department of Agricultural and Food Economics, University of Reading

Abstract

The adoption of organic production has increased dramatically over recent years, especially in less developed countries. However, little information is available about who adopts, the difficulties they face in converting and how these factors vary over time. Using small-scale avocado producers (<15ha) from Michoacán, Mexico as a case study, this paper explores the factors affecting the time-to-adoption of organic production and certification, drawing from five parametric descriptions of the data. These models are implemented using a Bayesian approach and advances in Markov chain Monte Carlo methods. The results indicate that additional sources of income, together with membership of producers' associations, higher levels of education and experience of export markets, other than the US, have a positive effect on the adoption decision. Labour requirements and administrative capacity appear to be unimportant, while information sources and the frequency of contact with these sources have a varied, but largely negative effect on the probability of adoption. These findings raise a number of questions about the future of organic production in Mexico and the avocado zone, not least how to overcome credit and information constraints, but more importantly whether aiming for the organic market is a viable production strategy for small-scale producers.

1. Introduction

A growing number of small-scale producers in less developed countries have been converting to organic agriculture and entering the global organic market. While spontaneous adoption has occurred, much of it can be attributed to the promotional efforts of environmental NGOs, church groups, government bodies and development agencies. This support is largely in response to the growth observed in the international organic food market following increased demand in Western countries. It is also seen as an opportunity to obtain premium prices for produce. Furthermore, organic production is commonly considered the epitome of sustainable agriculture, and increasingly the movement, is turning its focus to the inequalities generated through conventional production.

Recently, many studies have appeared in the literature investigating a variety of socio-economic aspects of organic agriculture. However, research on the motivation behind the adoption decision and the barriers to entry, is limited outside the grey literature, although a small number of studies do exist, largely focused on Europe and North America. These studies largely focus on the importance of input and output prices (e.g. Pietola and Lansink, 2001); differences in gross margins and the size of transaction costs in seeking out new markets and information (e.g. Musshoff and Odening, 2005); the characteristics of the farmer, such as education, household size and gender (e.g. Burton *et al.,* 1999, Egri 1999); and, increasingly on the role of information sources (e.g. Rigby, *et al.* 2001; Padel, 2001; Lohr and Salomonsson, 2000; Duram, 1999).

The literature on the adoption of sustainable agriculture and conservations methods in general presents similar results, however, lack of profitability and credit constraints are also cited as significant barriers (Cary and Wilkinson, 1997). In the context of developing countries, case study evidence does suggest that credit is an important constraint to conversion (for example, IFAD, 2005, 2003). Nevertheless, organic production has developed rapidly in some areas in spite of limited formal credit sources.

Also absent from the organics literature is any exploration of adoption over time and how the waiting times of farmers to adopt organic production differ. One notable exception is Burton *et al.* (2003). Using a Weibull form of a duration model and allowing a piecewise constant specification, they calculate the hazard ratio for different characteristics of British horticultural producers and their impact on the likelihood of adoption. The duration approach has also been used in a small number of similar agricultural technology adoption studies, for example, Caviglia and Kahn (2001) and de Sousa Filho *et al.* (1999) investigating the diffusion of sustainable agriculture technologies in Brazil; Carletto *et al.* (1999) exploring the diffusion of smallholder non-traditional agro-exports in Guatemala; and more recently, Dadi *et al*. (2004) on the analysis of technology adoption in Ethiopian agriculture. This approach has many advantages over the more common probit/logit methods as it relaxes the assumption of homogeneity within groups; the time to adoption (or the end of a particular state) can be captured, as can the effects of factors that change with time. This is extremely significant as technology adoption is a dynamic process that occurs gradually over what may be extended periods of time.

We now present the case of small-scale (<15ha) avocado production in Michoacán, Mexico. Our main interest lies in assessing the time-to-organic adoption among a sample of representative avocado producers from four main survey sites in Michoacán. Using a rich, 165-observation sample of organic and conventional producers, we investigate how a number of demographic and associated production characteristics influence the waiting time of farmers before making the decision to convert. In section two we present background to organic production in Mexico and the organic avocado industry in Michoacán. In section three we describe the data and in section four we introduce the econometric procedures for processing the data. The results of the econometric investigation are presented in section five and conclusions and extensions are presented in section six.

2. Organic Production in Mexico

Individual coffee growers and *finca* owners were the first to convert to organic production during the early 1980s. These were shortly followed by a number of large producers' associations of small-scale, indigenous coffee growers from Oaxaca and Chiapas, central and southern Mexico. The motives behind conversion were many. However, the unstable and falling global coffee prices were a key driver, as was the Catholic Church. The organic sector has since seen dramatic growth and Mexico has moved into first place globally in terms of the number of organic producers, with over 80 000, farming over 200 000 ha of land (Willer and Yussefi, 2007). Of these latter units, an estimated 98.6 percent are small-scale, farming about 84.1 percent of this land. Nevertheless, organic production remains the smallest sector in Mexico's agricultural industry constituting about 0.2 percent of total agricultural land and representing about 2 percent of producers (Gómez Cruz *et al*., 2002). Despite this small scale, organic production was valued at about US$ 280 million in 2002, or 8.5 percent of total agricultural income, 68.8 percent of which came from small-scale producers (Gómez Tovar and Gómez Cruz, 2004).

As with other less developed countries, organic production in Mexico is principally for export. Although estimates vary, anything between 80 to 85 percent (Gómez Cruz *et al.*, 2002) and 98 percent (OTA, 2004) of total organic produce leaves the country with the key markets being the USA and Europe. According to Gómez Cruz *et al.* (2002), the remaining 15 to 20 percent is sold on the conventional market or through the limited internal organic market. Organic production in Mexico is, nevertheless, expected to grow, driven by further export and increased demand from overseas markets (Leonard, 2005).

Organic avocados

In 2004 there were approximately 100 certified organic avocado producers ranging in scale from 1ha to 200ha. Of these, about 50 were members of an organic avocado producers' association, PRAGOR (Organic Avocado Producers). PRAGOR's roles include marketing fruit, provision of technical advice and bulk purchase of inputs. The remaining producers work individually, selling their fruit the best they can. Some small-scale producers are organised into groups to reduce the cost of certification, however, these groups are generally small, ranging from about five to ten members and are not concerned with the marketing of fruit.

According to Bioagricoop (the main certification body in the area), 10 887 tonnes of organic avocados were harvested from 1265 hectares during the 2003-2004 cycle, suggesting an average yield of 8.6 tonnes per hectare (compared to approximately 10 tonnes per hectare in conventional systems). Information provided by Mexican Avocados (the second most important packer of organic avocados) suggests that only about 30 percent of this was actually sold on the organic market. The remainder were sold on the conventional market as a consequence of quality control and supply being greater than demand.

Organic avocados receive a premium price that fluctuates between 20 and 30 percent depending on the location of the market. The US provides the highest premium and absorbs the highest share of organic avocado output, followed by Japan; however, these markets are the most demanding in terms of quality and size specifications. The European market receives little organic fruit due to difficulties in shipping, the absence of organic post-harvest management and lower prices.

Time-to-adoption

In considering different approaches to modelling the time element in this study and the associated issue of censoring of the data, it is important to define the time-to-adoption. Two logical definitions present themselves: The first definition can be thought of in terms of the time since the first producer gained organic certification, with a calendar year clock having started at this point (i.e. 1993). This approach assumes that the appearance of certified organic agriculture in Michoacán would have created a different set of completive options for avocado producers in the region which would have affected the time-to-certification. The maximum lifespan of an avocado producer would be 11 years and the minimum one year. The most interesting set of covariates might therefore be those observed during the first year of appearance of the individual producer in the dataset.

In the second case, time can be interpreted as the period of time that an individual has been producing avocados. Each individual therefore has his/her own individual calendar clock, left censoring is avoided and the situation is considerably simplified. This approach takes into account the individual time-to-adoption, and although it has only been during the last 11 years that producers have been converting, they have had the potential to do so before. We proceed with this interpretation and use covariates pertaining to observations in the last year that a producer is observed as 'conventional'.

3. Description of the data

This study uses data gathered principally in four municipalities in Michoacán, Mexico between June and August 2004. Fieldwork was executed in two main stages. First a qualitative stage of semi-structured interviews obtained general background information about the avocado industry, followed by a quantitative stage which involved an in depth household survey of the target population. As no accurate list of avocado producers was available for the study area, sampling proceeded by identifying, where possible, individuals from the list of producers registered with the State Committee for Phytosanitation, enquiring of these individuals the names of other producers and occasionally enlisting the assistance of the village or ejidal[1] authorities. Information, however, was much easier to obtain about organic farmers from certification bodies (although it was deemed, at times, to be somewhat unreliable). As the number of small-scale organic producers was relatively small, a census approach was taken and for every organic producer interviewed in a village, approximately three conventional producers were also interviewed. To ensure coverage of all small-scale organic producers, survey work focused on four municipalities: Uruapan, Periban, Tancítaro and Nuevo Parangaricutiro. Nevertheless, to obtain as many as possible of the organic producers, individual journeys were also made to other communities when necessary. Finally, 47 of the known 49 small-scale organic producers and 187 conventional producers were interviewed. It is a subset of these responses that is used in this paper.

The questionnaire collected socio-demographic data about the producer and his/her family; production statistics for the most recent production cycle and, thus, encompassed the four main harvests (July 2003 - June 2004); farm assets; access to information and credit sources; other income sources; and attitudes and beliefs about organic production. Not all of these data are included in this study. Table 1 presents the summary statistics of variables used in econometric analysis, classified by adoption status.

4. Methodology

We now turn to a description of the methods employed to analyze these data. We commence by considering the probability of observing a non-organic enterprise at time *t*. Following standard developments (see, for example, Ibrahim, Chen and Sinha (2001) in Bayesian mode and see Lancaster (1992) for a sampling theory treatment) assume that time *t*, if observed, is a realization from a random process $f(\mathrm{T}|\boldsymbol{\theta})$, where $f(\cdot)$ denotes a probability density function for the random variable T and $\boldsymbol{\theta} \equiv (\boldsymbol{\theta}_1, \boldsymbol{\theta}_2, .., \boldsymbol{\theta}_M)'$ denotes an M-vector of parameters conditioning $f(\cdot)$. Note that T is only observed for those individuals who leave the state (i.e. adopters); for censored individuals (i.e. non-adopters), T is at least *t*, but not equal to it. It follows that the probability of observing the realization *t* is

(1) $\mathrm{F(t)} = \int f(\mathrm{s})\mathrm{ds} = \mathrm{Prob(T} \le \mathrm{t)}.$

As noted by Greene (1997, p. 986), we will usually be more interested in the probability that the spell is of length at least as great as *t*, which is given by the *survival function*

(2) $\mathrm{S(t)} = 1 - \mathrm{F(t)} = \mathrm{Prob(T > t)}.$

Correspondingly, we are able to compute the instantaneous probability of failure, given that an individual has been a conventional producer at least as long as *t*. This probability is referred to as the *hazard rate* and gives rise to the *hazard function*

(3) $\mathrm{H(t)} = \lim_{\Delta t \to 0} \mathrm{Prob(t < T \le t+\Delta \mid T > t)} \div \Delta\mathrm{t} = f(\mathrm{T}|\boldsymbol{\theta}) \div \mathrm{S(t)}.$

The hazard function is important as an aid for interpreting the results of our econometric investigations because the effect on changes in survival are not available directly from the estimated covariate coefficients; manipulations of varying complexity are generally required and it is commonplace to define the responses in terms of their impacts on (3).

Primary interest lies in estimating and comparing the inferences derived from the parametric models that appear frequently in the empirical literature (see, Keifer (1988) and Lancaster (1992) for comparisons of the main parametric forms in the classical literature and see Ibrahim *et al.* (2001) for a review of recent Bayesian applications). These forms are *five* and are the probability models derived by assuming that the failure times $\mathbf{y} \equiv (\mathrm{y}_1, \mathrm{y}_2, .., \mathrm{y}_N)'$ are derived, respectively, from an Exponential probability density function (pdf), $f^{E}(\cdot|\lambda)$; the Weibull pdf, $f^{W}(\cdot|\alpha,\lambda)$; the extreme value pdf, $f^{V}(\cdot|\alpha,\lambda)$; the log-normal pdf, $f^{lN}(\cdot|\lambda,\tau)$; and the gamma pdf, $f^{G}(\cdot|\alpha,\lambda)$. Details of the densities are reported in the appendix.

To build regression-type models employing one of the five data-generating pdfs, we allow covariates to enter via the vector $\boldsymbol{\lambda} \equiv (\lambda_1, \lambda_2, .., \lambda_N)'$ and then parameterizing each of the individual-specific elements of $\boldsymbol{\lambda}$. Defining covariates through $\mathbf{X} \equiv (\mathbf{x_1}', \mathbf{x_2}', \ldots, \mathbf{x_N}')'$, $\mathbf{x_1} \equiv (x_{11}, x_{12}, \ldots, x_{1K})'$, $\mathbf{x_2} \equiv (x_{21}, x_{22}, \ldots, x_{2K})'$, .., and $\mathbf{x_N} \equiv (x_{N1}, x_{N2}, \ldots, x_{NK})'$, we use $\boldsymbol{\beta} \equiv (\beta_1, \beta_2, .., \beta_K)'$ to denote the vector of 'regression' coefficients. For example, to implement the Exponential regression model we parameterize $\boldsymbol{\lambda} \equiv (\exp(\mathbf{x_1}'\boldsymbol{\beta}), \exp(\mathbf{x_2}'\boldsymbol{\beta}), .., \exp(\mathbf{x_N}'\boldsymbol{\beta}))'$; and across the remaining specifications (Weibull, Extreme-value, log-Normal and Gamma specifications) we parameterize $\boldsymbol{\lambda} \equiv (\mathbf{x_1}'\boldsymbol{\beta}, \mathbf{x_2}'\boldsymbol{\beta}, .., \mathbf{x_N}'\boldsymbol{\beta})'$. To implement these models, we form a prior pdf over the parameters $\pi(\boldsymbol{\theta})$; form the likelihood $f(\mathbf{y}|\boldsymbol{\theta})$ for the observed duration data $\mathbf{y} \equiv (y_1, y_2, .., y_N)'$; and study the posterior distribution for the parameters

(4) $$\pi(\boldsymbol{\theta}|\mathbf{y}) \propto f(\mathbf{y}|\boldsymbol{\theta})\, \pi(\boldsymbol{\theta}),$$

where '$\propto$' denotes 'is proportional to.' In the case of the exponential model, $\boldsymbol{\theta} \equiv (\beta_1, \beta_2, .., \beta_K)'$; in the case of the log-normal model $\boldsymbol{\theta} \equiv (\tau, \beta_1, \beta_2, .., \beta_K)'$; and in the remaining cases $\boldsymbol{\theta} \equiv (\alpha, \beta_1, \beta_2, .., \beta_K)'$, where τ and α function as scale parameters affecting the patterns of time dependence. An important feature of duration studies is that some of the duration observations $\mathbf{y} \equiv (y_1, y_2, .., y_N)'$ will be *censored*. Specifically, if $\mathbf{t} \equiv (t_1, t_2, .., t_N)'$ denote the survival times of the individual producers in question and T denotes the endpoint of the study, then we observe $\mathbf{y} \equiv (\min(t_1,T), \min(t_2,T), .., \min(t_N,T))'$. To allow for censoring, we make use of the vector of binary indicators $\boldsymbol{\nu} \equiv (\nu_1, \nu_2, .., \nu_N)'$, where, for i = 1, 2, .., N, $\nu_i = 1$ if $t_i \leq T$, otherwise $\nu_i = 0$. Accordingly, the likelihood corresponding to a set of observed durations is

(5) $$f(\mathbf{y}|\boldsymbol{\theta}) \equiv \prod_i f(y_i|\boldsymbol{\theta})^{vi}\, S(y_i|\boldsymbol{\theta})^{(1-vi)}.$$

Details of the specific forms of $f(\mathbf{y}|\boldsymbol{\theta})$ that emerge from the Exponential, Weibull, Extreme-value and log-Normal specifications are presented in the appendix. Complexities encountered in the Gamma formulation make it easier to augment the model with latent data $\mathbf{z} \equiv (z_1, z_2, .., z_N)'$, where, for i = 1, 2, .., N, $z_i = y_i$ if y_i is a failure time, otherwise $z_i > y_i$. In this instance we work with the complete-data likelihood

(6) $$f(\mathbf{y}|\boldsymbol{\theta},\mathbf{z}) \equiv \prod_i f(y_i|\boldsymbol{\theta},\mathbf{z})^{vi}\, S(y_i|\boldsymbol{\theta},\mathbf{z})^{(1-vi)}.$$

Details of $f(\mathbf{y}|\boldsymbol{\theta},\mathbf{z})$ for the Gamma assumption are presented in the appendix.

As each specification has an *unknown integrating constant*, we employ Markov Chain Monte Carlo (*MCMC*) methods. Ibrahim *et al.* suggest exploiting the log-concavity of posterior pdfs and employing the adaptive-rejection sampling algorithm of Gilks and Wild

(1992). Alternatively, we find that simple, *random-walk, Metropolis-Hastings algorithms* work very well. This approach has the advantage of permitting straightforward model comparison.

Detailed expressions of the five algorithms can be found in the appendix, each of them differing in terms of the likelihoods, but also by the number of unknowns in question and the corresponding numbers of draws required. The algorithm for the Exponential model is the simplest. It can be explained, with reference to the prior information over the regression coefficients, $\pi(\boldsymbol{\beta})$; the likelihood, $f^{E}(y|\boldsymbol{\beta})$, which is defined in the appendix; and a proposal density for the coefficients in question that is conditioned by the current or 'state' value of their values which is the multivariate-Normal density, $f^{mN}(\boldsymbol{\delta}|\boldsymbol{\beta},\boldsymbol{\Omega}\times\xi)$. In this expression $\boldsymbol{\delta} \equiv (\delta_1, \delta_2, .., \delta_K)'$ denotes a multi-variate draw of the same length as $\boldsymbol{\beta}$; and $\boldsymbol{\Omega}$ and ξ denote 'tuning parameters' designed to adjust the covariance for $\boldsymbol{\delta}$ during the search for $\boldsymbol{\beta}$. With these inputs at hand, the algorithm for simulating draws from the posterior derived from the Exponential model consists of iterating the following steps:

A_1: Exponential Algorithm: Simulate a draw from $f^{mN}(\boldsymbol{\delta}|\boldsymbol{\beta},\boldsymbol{\Omega}\times\xi^2)$ and accept the draw with probability $\wp \equiv \min\{[f^{E}(\mathbf{y}|\boldsymbol{\delta})\ \pi(\boldsymbol{\delta})] \div [f^{E}(\mathbf{y}|\boldsymbol{\beta})\ \pi(\boldsymbol{\beta})],1\}$.

Thus the algorithm for the exponential model is surprisingly simple. A starting value is chosen for $\boldsymbol{\beta}$; the covariance terms $\boldsymbol{\Omega}$ and ξ are adjusted according to a convergence criterion; and a period of burn-in is executed before the $\{\boldsymbol{\beta}^{(g)}$, s = 1, 2, .., G$\}$ obtained from the iterations can be considered draws from a stable target distribution. In theory the choice of start vector for $\boldsymbol{\beta}$ is immaterial because the algorithm should be iterated for G sufficiently large that inferences are independent of any start value; however, in practice, we set $\boldsymbol{\beta}^{(0)} = \mathbf{0_K}$. Second, we set $\boldsymbol{\Omega} = (\mathbf{X}'\mathbf{X})^{-1}$ and permit ξ (>0) to adjust so that the 'acceptance rate' of draws for $\boldsymbol{\beta}$ is $\wp = .25$. This choice is quite arbitrary; however, we find that this choice works well in all simulations. Finally, we set G = 100,000 and collect this sample following an initial 'burn-in' of S = 100,000.

The second algorithm we employ pertains to the Weibull model. Unlike the Exponential model, which consists of a single parametric 'block,' the Weibull model contains an additional parameter, namely α. The Exponential model is nested as a special case of the Weibull model in which $\alpha = 1$. Consequently, some interest centres on assessing the location of the posterior relative to the value one. With an additional parametric block in place, the

Weibull algorithm consists of an additional step and can be summarized, relegating details to the appendix, as follows:

> A_2: Weibull Algorithm: Simulate a draw from $f^{mN}(\boldsymbol{\delta}|\boldsymbol{\beta},\boldsymbol{\Omega}\times\xi^2)$ and accept the draw with probability $\wp_{\boldsymbol{\beta}} \equiv \min\{[f^W(\mathbf{y}|\alpha,\boldsymbol{\delta})\ \pi(\boldsymbol{\delta})] \div [f^W(\mathbf{y}|\alpha,\boldsymbol{\beta})\ \pi(\boldsymbol{\beta})],1\}$. Simulate a draw from $f^{tN}(\gamma|\alpha,\eta^2,0)$ and accept the draw with probability $\wp_\alpha \equiv \min\{[f^W(\mathbf{y}|\gamma,\boldsymbol{\beta})\ \pi(\gamma) \div f^{tN}(\gamma|\alpha,\eta^2,0)] \div [f^W(\mathbf{y}|\alpha,\boldsymbol{\beta})\ \pi(\boldsymbol{\beta}) \div f^{tN}(\alpha|\gamma,\eta^2,0)],1\}$.

As with the Exponential distribution, we employ $\boldsymbol{\beta}^{(0)} = \mathbf{0_K}$; permit ξ to vary in order to target $\wp_{\boldsymbol{\beta}} = .25$; and set S = 100,000 for both the 'burn-in' and the 'sample' phases of the iterations. In addition we permit η to vary in order to target $\wp_\alpha = .25$.

The algorithms for the Extreme-value and log-Normal models are essentially the same. For the Extreme-value model we use:

> A_3: Extreme-Value Algorithm: Simulate a draw from $f^{mN}(\boldsymbol{\delta}|\boldsymbol{\beta},\boldsymbol{\Omega}\times\xi^2)$ and accept the draw with probability $\wp_{\boldsymbol{\beta}} \equiv \min\{[f^V(\mathbf{y}|\alpha,\boldsymbol{\delta})\ \pi(\boldsymbol{\delta})] \div [f^V(\mathbf{y}|\alpha,\boldsymbol{\beta})\ \pi(\boldsymbol{\beta})],1\}$. Simulate a draw from $f^{tN}(\gamma|\alpha,\eta^2,0)$ and accept the draw with probability $\wp_\alpha \equiv \min\{[f^V(\mathbf{y}|\gamma,\boldsymbol{\beta})\ \pi(\gamma) \div f^{tN}(\gamma|\alpha,\eta^2,0)] \div [f^V(\mathbf{y}|\alpha,\boldsymbol{\beta})\ \pi(\boldsymbol{\beta}) \div f^{tN}(\alpha|\gamma,\eta^2,0)],1\}$.

And for the log-Normal model we employ:

> A_4: Log-Normal Algorithm: Simulate a draw from $f^{mN}(\boldsymbol{\delta}|\boldsymbol{\beta},\boldsymbol{\Omega}\times\xi^2)$ and accept the draw with probability $\wp_{\boldsymbol{\beta}} \equiv \min\{[f^{lN}(\mathbf{y}|\tau,\boldsymbol{\delta})\ \pi(\boldsymbol{\delta})] \div [f^{lN}(\mathbf{y}|\tau,\boldsymbol{\beta})\ \pi(\boldsymbol{\beta})],1\}$. Simulate a draw from $f^{tN}(\rho|\tau,\eta^2,0)$ and accept the draw with probability $\wp_\tau \equiv \min\{[f^{lN}(\mathbf{y}|\rho,\boldsymbol{\beta})\ \pi(\rho) \div f^{tN}(\rho|\tau,\eta^2,0)] \div [f^{lN}(\mathbf{y}|\tau,\boldsymbol{\beta})\ \pi(\boldsymbol{\beta}) \div f^{tN}(\tau|\rho,\eta^2,0)],1\}$.

Finally, the algorithm for the Gamma model is only slightly more complicated due to the presence of an additional step to draw the latent data. Recalling that $\mathbf{z} \equiv (z_1, z_2, .., z_N)'$ denotes both observed and latent data, such that, $z_i = y_i$ if $\nu_i = 1$ and $z_i > y_i$ if $\nu_i = 0$, the algorithm consists of the three steps:

> A_5: Gamma Algorithm: Simulate a draw from $f^{mN}(\boldsymbol{\delta}|\boldsymbol{\beta},\boldsymbol{\Omega}\times\xi^2)$ and accept the draw with probability $\wp_{\boldsymbol{\beta}} \equiv \min\{[f^G(\mathbf{y}|\alpha,\boldsymbol{\delta})\ \pi(\boldsymbol{\delta})] \div [f^G(\mathbf{y}|\alpha,\boldsymbol{\beta})\ \pi(\boldsymbol{\beta})],1\}$. Simulate a draw from $f^{tN}(\gamma|\alpha,\eta^2,0)$ and accept the draw with probability $\wp_\alpha \equiv \min\{[f^G(\mathbf{y}|\gamma,\boldsymbol{\beta})\ \pi(\gamma) \div f^{tN}(\gamma|\alpha,\eta^2,0)] \div [f^G(\mathbf{y}|\alpha,\boldsymbol{\beta})\ \pi(\boldsymbol{\beta}) \div f^{tN}(\alpha|\gamma,\eta^2,0)],1\}$. For each i $\in$ **c**, simulate a draw

from $f^{tG}(z_i|\alpha,\boldsymbol{\beta},y_i)$ and accept the draw with probability $\wp_{zi} \equiv 1$.

The reader will note that we accept the draws for the last step with probability one. This case differs from the other situations in which we adjust a covariance term to target a particular acceptance rate. Indeed, the fully conditional distribution for the censored observations of the Gamma model are available in closed form and are known to be truncated-Gamma in form.

Prior Information

In considering prior information, non-data information about the locations and scales of the distributions for the regression coefficients is decidedly weak. There are two reasons. First, we are unable to locate previous studies of the organic avocado industry in which duration models have been employed; second, prior elicitation of regression coefficients in economic duration studies is complicated by the facts that, except for one case (the Exponential model) their relationship to readily intuitive notions such as the 'hazard rate' is indirect. For this reason the prior that we use with respect to the regression coefficients is weakly informative but proper. In particular, inferences are made with respect to the assumption $f^{mN}(\boldsymbol{\beta}|\boldsymbol{\beta}_o,\mathbf{C}_o)$, $\boldsymbol{\beta}_o = \mathbf{0}_K$ and $\mathbf{C}_o = \mathbf{I}_K \times 100$. Experiments with this formulation suggest that it is sufficiently weak to allow the data to dominate posterior inference but, by virtue of the fact that it is proper, is sufficient to enable formal model comparisons. In the context of the exponential model this prior is all that is required in order to implement the estimation algorithm; in the remaining cases we also require priors on the 'scale' parameters α and τ. We employ the gamma priors $f^G(\alpha|\alpha_o,\kappa_o)$, $\alpha_o = 1$, $\kappa_o = 1$; and $f^G(\tau|\alpha_o,\lambda_o)$, $\alpha_o = 1$, $\lambda_o = 1$.

Model Comparison

In cases where alternative specifications generate distinctive inferences it is useful to have available a method for discriminating between them. A simple modification to the structure of the MCMC algorithm makes it possible to obtain accurate estimates of model marginal likelihoods, which are the essential inputs in Bayesian model comparison (Chib, 1995; Chib and Jeliazkov, 2001). In this section we briefly outline the modifications that are necessary to perform model selection.

Given an arbitrary model specification, $\mathbf{m}$, the essential observation stems from rewriting *the basic marginal likelihood identity*

(7) $\quad m(\mathbf{y}|\mathbf{m}) \; = \; f(\mathbf{y}|\boldsymbol{\theta}^*,\mathbf{m}) \times \pi(\boldsymbol{\theta}^*) \div \pi(\boldsymbol{\theta}^*|\mathbf{y},\mathbf{m})$,

and placing it on the computationally convenient logarithmic scale,

(8) $\quad \log m(\mathbf{y}|\mathbf{m}) \; = \; \log f(\mathbf{y}|\boldsymbol{\theta}^*,\mathbf{m}) + \log \pi(\boldsymbol{\theta}^*) - \log \pi(\boldsymbol{\theta}^*|\mathbf{y},\mathbf{m})$.

Here $\boldsymbol{\theta}^*$ denotes an arbitrary point in the parameter space. Because this identity holds at any point in that space the choice of $\boldsymbol{\theta}^*$ is indeed arbitrary although, in practice, we usually pick a high-density value, such as the posterior mean or the maximum likelihood point. It follows naturally that estimating the marginal likelihood reduces to a problem of estimating the three quantities on the right side of (8).

The case where the parameters $\boldsymbol{\theta}$ consist of a single block as, for example, in the exponential model, is given by Chib and Jeliazkov (pp. 271-272). The first quantity on the right-hand side of (8) is available directly. Similarly, the second quantity is available once the prior is completely specified. The third quantity, the posterior pdf evaluated at the point $\boldsymbol{\theta}^*$, is estimated by first decomposing the quantity of interest into the ratio of two expectations (Chib and Jeliazkov, p. 271). The expectation in the numerator of this ratio is obtained as part of the usual Gibbs run. To obtain an estimate of the expectation in the denominator we hold constant $\boldsymbol{\theta}^*$ and simulate values of $\boldsymbol{\theta}$ conditional on this fixed value $\boldsymbol{\theta}^*$. At the end of this reduced run an estimate of this third quantity is available and model comparison is possible. Estimates of the posterior quantities corresponding to the remaining models are available from extending the algorithm in similar fashion. Details are presented in Chib and Jeliazkov (pp. 272-273). Finally, it is possible to place a (numerical) standard error on the calculation so obtained using results for heteroscedastic covariance estimation (Newey and West, 1987).

5. Empirical Results

The results from the five different specifications of the duration model estimation are presented in table 2. The first row reports the scale parameter (absent for the exponential model) and illustrates a positive time dependence for all models. For each covariate the posterior mean is reported and, in parenthesis, the 95 percent highest posterior density interval. Intervals that do not cross zero indicate a significant covariate. Model diagnostics can be found at the bottom of the table.

Comparison of the five formulations of the duration model and examination of the log marginal likelihood clearly indicates the Weibull model as the preferred specification, followed by the Extreme Value model. The low numerical standard error for the Weibull model also suggests a high degree of reliability in this specification. The log normal specification appears to be the poorest formulation for modelling this data. However, if we compare the logarithm of the predicted and observed duration times of the Weibull model (see figure 1) we find that it generally overestimates the duration, suggesting a poor fit to the data. The implication of this for the hazard rate can be seen in figure 2, where there is a particularly poor fit at high and low values of the hazard, the reason for which is unclear. Nevertheless, in view of the present case study, the following discussion will focus on the findings from the Weibull model alone.

As table 2 illustrates, 20 of the covariates in the Weibull model have a significant effect on the time-to-organic production, seven of which have a positive impact, thereby increasing the conditional probability of conversion. These include talking with other organic producers about the management of avocado orchards; having other income sources including producing another crop, having other off-farm employment and having received credit at some point in the past. Membership of a producers' association, having a higher level of education and having export experience of markets other than the US are also positive influences.

Other factors which might have been expected to have a positive influence, such as different sources of orchard management information (from agronomists, other producers, the State Phytosanitary Committee and publications) and the frequency of contact with these information sources actually have a negative impact on the hazard, reducing the probability of conversion. Other covariates that also reduce the probability of conversion include location variables for Uruapan, Periban, Tancítaro and 'other locations', being an owner of the orchard and the size (in hectares) of the orchard, receiving remittances and age. A number of covariates, including being located in Nuevo Parangaricutiro, the total farm size, having heard of organic and knowing organic farmers, exporting to the US, the labour requirement for an orchard and keeping a management plan do not have a significant effect on the probability of conversion.

It is clear from these results that producers who enter the organic market are distinct from other producers, but that they do not confirm all the findings from earlier studies, a particular difference being the role of a diversity of information sources. Throughout the avocado zone, access to reliable sources of information about organic production of avocados is limited. Only a small number of agronomists are trained in organic production and much has been discovered about organic methods through informal experimentation by farmers themselves. In addition, the local university and INIFAP (a government sponsored research body) did not provide training or carry out research into organic avocado production at the time. In the absence of widespread information about organic production, it is not entirely surprising that the information sources currently available have a negative impact on the probability of adoption. Farmers are unable to gather sufficient information to reduce the uncertainty surrounding the new techniques and consequently do not wish to risk the conversion process. However, figure 3 plots the effect of one extra unit of information from 'other' sources on the hazard rate and suggests that this change would positively influence the conversion rate. Nevertheless, some producers are able to gather sufficient information, perhaps by talking to other organic producers; they also appear more dependent on diverse income sources, such as off-farm employment and other crops. This suggests that they have an increased ability to invest in the face of risk and uncertainty, from both financial and production sources. The fact that they have received credit suggests that their ability to cope with risk through a strong asset base, one allowing them to comply with borrowing requirements, is important. For organic producers coping with risk will be especially important during the initial stages of conversion to organic methods. Producers not only have to learn new management techniques (which may or may not function successfully), but they also face potentially declining yields and are unable to sell their fruit under the organic label. For an individual relying on avocado production as a sole income for his/her family, such risks may be too great to bear.

The paucity of information and the financial risks are not the only uncertainties facing potential organic producers. The producer also faces high transaction costs in the identification of new buyers and markets. Many organic producers have overcome this problem through the membership of a producers' association, a factor which has a positive impact on the probability of conversion. Such associations remove the market identification transaction costs by taking responsibility for the identification of buyers and, equally as importantly, securing the volume of fruit required by the purchaser. Furthermore, in the absence of formal contracts, selling through a producers' association also removes the effort necessary for building individual trust relationships between buyer and seller. Evidence of the role of producers' associations is further supported by other examples from organic production in Mexico, such as organic vegetables (Marsh and Runsten, 2002) and coffee (Barton Bray et al., 2002).

The fact that non-household labour requirements have no significant impact on the probability of adoption is interesting. Organic production, like other conservation technologies, is commonly assumed more labour intensive, for example, Barton Bray *et al.* (2002) find for organic coffee growers in Chiapas, that more labour is demanded. However, this is largely met by household sources and offsets the need to search for off-farm employment. The case may be similar for avocado production, whereby additional labour requirements are met by family members, rather than other sources, especially given the relatively expensive nature of non-family labour (approximately US$10.7 per day).

The other results are generally as expected with younger, more educated individuals being the most likely to adopt first. Older farmers are often shown less likely to adopt new technologies and education is routinely shown to be a key variable in the adoption of new technologies (Feder *et al.*, 1985). Furthermore, as organic production necessitates greater administrative transparency, higher levels of literacy are expected to be beneficial. This is also consistent with the literature on the adoption of organic management in developed countries (e.g. Burton *et al.*, 2003; Padel, 2001).

There is some contention, however in the organics literature about the impact of farm size on adoption. Padel (2001) and Burton *et al.* (1999) state that organic holdings tend to be smaller than their conventional counterparts, but evidence from Mexican organic coffee growers shows that within the category of small-scale, it is the larger producers who adopt (Barton Bray *et al.*, 2002). This study however, suggests that smaller-scale producers are more likely to adopt before producers with a larger avocado area decide to adopt. This may be significant for future strategies in the avocado zone given the very large number of small-scale producers.

A present strategy within the avocado zone is to encourage producers to meet the phytosanitary and quality conditions necessary for the entry into the US market. This provides an explanation of why exporting to the US market is not significant to the adoption of organic production. However, exporting to other countries does have a positive influence, suggesting the experience gained of alternative markets is essential and illustrates how organic farmers are required to search more widely for markets. Interestingly though, physical location of the orchard has a negative effect on the hazard. It is unlikely that location bears much influence on market penetrations as moving fruit from orchards is often the responsibility of the packer, rather than the producer. The negative affect of location might be more related to flows of information and lack of knowledge about organic production throughout the avocado zone.

6. Conclusions

This study explores the factors affecting the probability of adoption of organic production by small-scale avocado producers in Michoacán, Mexico. The duration approach has been shown useful to the exercise; however, it is constrained by the assumption that, as some point in time, all producers will adopt organic production. This assumption is clearly unlikely; technology adoption is rarely a complete process. We therefore propose a straight-forward extension in which we incorporate an additional equation representing a hurdle that nets out all of those producers who would never become organic.

Duration analysis can also capture the effects of time-varying covariates; however, we are unaware of any examples in the literature using a Bayesian approach. This again limits the present study, but the future addition of a piecewise continuous function may facilitate their inclusion. This would allow a better understanding of how the developing organic market may be influencing the adoption decision of avocado producers.

Nevertheless, the results from the present study have been enlightening and raise a number of questions about the future of organic farming in the avocado zone, but also in Mexico in general. First, how to overcome the credit constraints facing many small-scale producers? Second, how best to fill the information void and where to target the information flow? Third, how can organisation of small-scale growers be encouraged to facilitate entry into the organic market? Fourth, and perhaps most importantly, should organic production be promoted at all to small-scale producers?

Organic avocado production is still considered in its incipient stages and faces a number of challenges if wide-spread adoption is to occur. Some producers would require a great deal of assistance in reaching the organic market, but greater benefit might be achieved through the promotion of improved management techniques and enlightened agrochemical use. Any program aimed at helping small-scale avocado producers should focus on basic agronomy and pest control, whether organic or not.

This is not to say that organic production should not be promoted at all. The spontaneous adoption and growth in the sector without external support should be encouraged, as such support could greatly enhance the welfare of those individuals closer to the ‘threshold of conversion’. However, a greater appreciation of who benefits from the adoption of organic production is needed, as is a better understanding of what organic production can achieve in terms of rural development and improved incomes for small-scale producers.

Notes

1. The ejido refers to a system of land tenure governed by Article 27 of the 1917 Constitution. This Article led to redistribution of land to the peasantry, the emphasis of which being subsistence and social justice. The ejidal authorities are elected representatives who

take decisions regarding ejidal matters.

Appendix

<u>Pdfs</u>

The *nine* pdfs that we reference are:

1) the exponential pdf, $f^{E}(v|\lambda) \equiv \lambda\exp\{-\lambda v\}$, $0 < v < +\infty$, $0 < \lambda < +\infty$;
2) the Weibull pdf, $f^{W}(v|\alpha,\lambda) \equiv \alpha v^{\alpha-1}\exp\{\lambda-\exp\{\lambda\}v^{\alpha-1}\}$, $0 < v < +\infty$, $0 < \alpha < +\infty$, $0 < \lambda < +\infty$;
3) the extreme value pdf, $f^{V}(v|\alpha,\lambda) \equiv \alpha\exp\{\alpha v\}\exp\{\lambda-\exp\{\lambda+\alpha v\}$, $0 < v < +\infty$, $0 < \alpha < +\infty$, $0 < \lambda < +\infty$;
4) the log-normal pdf, $f^{lN}(v|\lambda,\tau) \equiv 2\pi^{-.5}\ y_i^{-1}\ \tau^{.5}\ \exp\{-.5\tau(\log(v)-\mu)^2\}$, $0 < v < +\infty$, $0 < \tau < +\infty$, $0 < \lambda < +\infty$;
5) the gamma pdf, $f^{G}(v|\alpha,\lambda) \equiv \Gamma(\alpha)^{-1}\ v^{\alpha-1}\ \exp\{\alpha\lambda-v\exp\{\lambda\}\}$, $0 < v < +\infty$, $0 < \alpha < +\infty$, $0 < \lambda < +\infty$;
6) the truncated-gamma pdf, $f^{tG}(v|\alpha,\lambda,h) \equiv \Gamma(\alpha)^{-1}\ (1-IG(\alpha,h\times\exp(\lambda)))^{-1}\ v^{\alpha-1}\ \exp\{\alpha\lambda-v\exp\{\lambda\}\}$, $h < v < +\infty$, $0 < \alpha < +\infty$, $0 < \lambda < +\infty$, where $IG(\alpha,h\times\exp(\lambda)) \equiv \Gamma(\alpha)^{-1} \int$ (from 0 to $h\times\exp(\lambda)$) $u^{\alpha-1}\ \exp\{-u\}\ d_u$ denotes the incomplete Gamma function;
7) the univariate-Normal pdf, $f^{N}(v|\mu, \sigma) \equiv (2\pi)^{-½}\ \sigma^{-1}\ \exp\{\ -½\ \sigma^{-2}\ (v-\mu)'\ (v-\mu)\ \}$, $-\infty < v < +\infty$, $-\infty < \mu < +\infty$, $0 < \sigma < +\infty$;
8) the truncated-Normal pdf, $f^{tN}(v|\mu, \sigma, h) \equiv (2\pi)^{-½}\ \sigma^{-1}\ \exp\{\ -½\ \sigma^{-2}\ (v-\mu)'\ (v-\mu)\ \}[1-\Phi((h-\mu)/\sigma)]^{-1}$, $h < v < +\infty$, $-\infty < \mu < +\infty$, $0 < \sigma < +\infty$, where $\Phi(\cdot)$ denotes the cdf corresponding to the standard normal pdf; and
9) the multivariate-Normal pdf $f^{mN}(\mathbf{v}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) \equiv (2\pi)^{-m/2}\ |\Sigma|^{-1/2}\ \exp\{\ -½\ (\mathbf{v}-\boldsymbol{\mu})'\ \Sigma^{-1}\ (\mathbf{v}-\boldsymbol{\mu})\ \}$, $\mathbf{v} \equiv (v_1, v_2, .., v_m)'$, $\boldsymbol{\mu} \equiv (\mu_1, \mu_2, .., \mu_m)'$, $-\infty < v_i < +\infty$, $-\infty < \mu_i < +\infty$, $i = 1, 2, m$ where $\boldsymbol{\Sigma}$ is an $m\times m$ positive definite symmetric (pds) matrix.

<u>Likelihoods:</u>

The observed-data likelihoods corresponding to text equation (5) are for the Exponential, Weibull, Extreme-value and log-Normal *regression models* are:

Exponential: $f^{E}(\mathbf{y}|\boldsymbol{\beta}) \propto \exp\{\Sigma_i v_i \mathbf{x_i}'\boldsymbol{\beta}\}\ \exp\{-\Sigma_i y_i \exp\{\mathbf{x_i}'\boldsymbol{\beta}\}\}$;

Weibull: $f^{W}(\mathbf{y}|\alpha,\boldsymbol{\beta}) \propto \alpha^{d} \exp\{\Sigma_i(\nu_i\mathbf{x_i}'\boldsymbol{\beta} + \nu_i(\alpha\text{-}1)\log(y_i) - y_i^{\alpha} \exp\{\mathbf{x_i}'\boldsymbol{\beta}\})\}$;

Extreme-value: $f^{V}(\mathbf{y}|\alpha,\boldsymbol{\beta}) \propto \alpha^{d} \exp\{\Sigma_i\nu_i(\mathbf{x_i}'\boldsymbol{\beta} + \alpha y_i) - \exp\{\mathbf{x_i}'\boldsymbol{\beta} + \alpha y_i\}\}$;

Log-Normal $f^{lN}(\mathbf{y}|\tau,\boldsymbol{\beta}) \propto \tau^{d/2} \exp\{-.5\tau\Sigma_i\nu_i(\log(y_i) - \mu)^2\} \times \prod_i y_i^{-\nu i} (1\text{-}\Phi(\tau^{.5} (\log(y_i)\text{-}\mathbf{x_i}'\boldsymbol{\beta})))^{1\text{-}\nu i}$;

The complete-data likelihood corresponding to the Gamma model is $f^{G}(\mathbf{y}|\alpha,\boldsymbol{\beta},\mathbf{z}) \propto \Gamma(\alpha)^{-d} \exp\{\Sigma_i\nu_i\alpha\mathbf{x_i}'\boldsymbol{\beta} + \Sigma_i((\alpha\text{-}1)\log(z_i) - z_i \exp\{\mathbf{x_i}'\boldsymbol{\beta}\})\}$.

Posterior forms

It follows that, given the prior pdfs $f^{mN}(\boldsymbol{\beta}|\boldsymbol{\beta}_\mathbf{o},\mathbf{C_o})$, $\boldsymbol{\beta}_\mathbf{o} = \mathbf{0_K}$ and $\mathbf{C_o} = \mathbf{I_K} \times 100$; $f^{G}(\alpha|\alpha_o,\kappa_o)$, $\alpha_o = 1$, $\kappa_o = 1$; and $f^{G}(\tau|\alpha_o,\lambda_o)$, $\alpha_o = 1$, $\lambda_o = 1$; the posterior forms corresponding to algorithms A_1, A_2, A_3, A_4 and A_5 are, respectively,

Exponential: $\pi(\boldsymbol{\theta}) \propto f^{E}(\mathbf{y}|\boldsymbol{\beta}) \times f^{mN}(\boldsymbol{\beta}|\boldsymbol{\beta}_\mathbf{o},\mathbf{C_o})$;

Weibull: $\pi(\boldsymbol{\theta}) \propto f^{W}(\mathbf{y}|\alpha,\boldsymbol{\beta}) \times f^{mN}(\boldsymbol{\beta}|\boldsymbol{\beta}_\mathbf{o},\mathbf{C_o}) \times f^{G}(\alpha|\alpha_o,\kappa_o)$;

Extreme-value: $\pi(\boldsymbol{\theta}) \propto f^{V}(\mathbf{y}|\alpha,\boldsymbol{\beta}) \times f^{mN}(\boldsymbol{\beta}|\boldsymbol{\beta}_\mathbf{o},\mathbf{C_o}) \times f^{G}(\alpha|\alpha_o,\kappa_o)$;

Log-Normal: $\pi(\boldsymbol{\theta}) \propto f^{lN}(\mathbf{y}|\tau,\boldsymbol{\beta}) \times f^{mN}(\boldsymbol{\beta}|\boldsymbol{\beta}_\mathbf{o},\mathbf{C_o}) \times f^{G}(\tau|\alpha_o,\lambda_o)$; and

Gamma: $\pi(\boldsymbol{\theta}) \propto f^{G}(\mathbf{y}|\alpha,\boldsymbol{\beta},\mathbf{z}) \times f^{mN}(\boldsymbol{\beta}|\boldsymbol{\beta}_\mathbf{o},\mathbf{C_o}) \times f^{G}(\alpha|\alpha_o,\kappa_o)$.

Hazard functions

The hazard functions corresponding to each model are, respectively:

Exponential: $H^{E}(y_i|\boldsymbol{\theta}) \equiv \exp(\mathbf{x}_i'\boldsymbol{\beta})$;

Weibull: $H^{W}(y_i|\boldsymbol{\theta}) \equiv \alpha\, y_i^{\alpha-1} \exp(\exp(\mathbf{x}_i'\boldsymbol{\beta}) - \exp(\mathbf{x}_i'\boldsymbol{\beta})\, y^{\alpha})$;

Extreme-Value: $H^{V}(y_i|\boldsymbol{\theta}) \equiv \alpha \exp(\alpha y_i) \exp(\mathbf{x}_i'\boldsymbol{\beta})$;

Log-Normal: $H^{lN}(y_i|\boldsymbol{\theta}) \equiv (2\pi)^{-1/2}\, y_i^{-1}\, \tau^{1/2} \exp\{-.5\tau\, (\log(y_i)\text{-}\mathbf{x}_i'\boldsymbol{\beta})^2\}$; and

Gamma: $H^{G}(y_i|\boldsymbol{\theta}) \equiv (2\pi)^{-1/2}\, y_i^{-1}\, \tau^{1/2} \exp\{-.5\tau\, (\log(y_i)\text{-}\mathbf{x}_i'\boldsymbol{\beta})^2\}$.

Comparative statics

It follows that, across each of the five models, the comparative-static responses of changes in the hazard rate with respect to a change in a covariate, symbolically $\delta_{ij} \equiv \partial H(y_i|\boldsymbol{\theta})/\partial x_{ij}$, are, respectively, Exponential: $\delta^{E}_{ij} \equiv \boldsymbol{\beta}_j \exp(\mathbf{x}_i'\boldsymbol{\beta})$;

Weibull: $\delta^{W}_{ij} \equiv \boldsymbol{\beta}_j \exp(\mathbf{x}_i'\boldsymbol{\beta})\ \alpha y_i^{\alpha-1}$;

Extreme-Value: $\delta^{V}_{ij} \equiv \boldsymbol{\beta}_j \exp(\mathbf{x}_i'\boldsymbol{\beta})\ \alpha \exp(\alpha y_i)$;

Log-Normal: $\delta^{lN}_{ij} \equiv [[f^{lN}(\mathbf{y}|\tau,\boldsymbol{\beta}) + S^{lN}(\mathbf{y}|\tau,\boldsymbol{\beta})] \div S^{lN}(\mathbf{y}|\tau,\boldsymbol{\beta})^2] \times f^{lN}(\mathbf{y}|\tau,\boldsymbol{\beta}) \times \tau \times (\mathbf{x}_i'\boldsymbol{\beta} - \log(y_i))$ β_j;

Gamma: $\delta^{G}_{ij} \equiv [[f^{G}(\mathbf{y}|\tau,\boldsymbol{\beta}) + S^{G}(\mathbf{y}|\tau,\boldsymbol{\beta})] \div S^{G}(\mathbf{y}|\tau,\boldsymbol{\beta})^2] \times f^{G}(\mathbf{y}|\tau,\boldsymbol{\beta}) \times \Gamma(\alpha)^{-1} \times y_i^{\alpha-1} \times \exp(\alpha\mathbf{x}_i'\boldsymbol{\beta} - y_i \exp(\mathbf{x}_i'\boldsymbol{\beta})) \times (\alpha\beta_j - y_i \exp(\mathbf{x}_i'\boldsymbol{\beta})\ \beta_j)$.

References

Barton Bray, D., J. L. Plaza Sánchez and E. Contreras Murphy (2002) Social dimensions of organic coffee production in Mexico: Lessons for eco-labelling. *Society and Natural Resources* 15, 429-446.

Burton, M., D. Rigby and T. Young (2003) Modelling the adoption of organic horticultural technology in the UK using duration analysis. *The Australian Journal of Agricultural and Resource Economics.*

Feder, G., R. E. Just and D. Zilberman (1985) Adoption of agricultural innovations in developing countries: a survey. *Economic Development and Cultural Change* 33, 255-297.

Burton, M., D. Rigby and T. Young (1999) Analysis of the determinants of adoption of organic horticultural techniques in the UK. *Journal of Agricultural Economics* 50(1), 47-63.

Carletto, C., A. de Janvry and A. Sadoulet (1999) Sustainability in the diffusion of innovations: Smallholder nontraditional agro-exports in Guatemala. *Economic Development and Cultural Change* 47(1), 345-369.

Cary, J. W. and R. L. Wilkinson (1997) Perceived profitability and farmers' conservation behaviour. *Journal of Agricultural Economics* 48(1), 13-21.

Egri, C. P. (1999) Attitudes, background and information preferences of Canadian organic and conventional farmers. *Journal of Sustainable Agriculture* 13(3), 45-73.

Chib, S. and E. Greenberg (1995) Understanding the Metropolis-Hastings Algorithm. *The American Statistician* 49, 327-335.

Chib, S. and I. Jeliazkov (2001) Marginal Likelihood From the Metropolis-Hastings Output, *Journal of the American Statistical Association*, 96, 270-81.

Dadi, L., M. Burton and A. Ozanne (2004) Duration analysis of technological adoption in Ethiopian agriculture. *Journal of Agricultural Economics* 55(3), 613-631.

de Souza Filho, H. M., T. Young and M. P. Burton (1999) Factors influencing the adoption of sustainable agriculture technologies: evidence from the state of Espírito Santo, Brazil. *Technical Forecasting and Social Change* 60, 97-112.

Duram, L. A. (1999) Factors in organic farmers' decision making: Diversity, challenge and obstacle. *American Journal of Alternative Agriculture* 14(1), 2-10.

Gilks, W.R., and P. Wild, (1992) Adaptive Rejection Sampling for Gibbs Sampling, *Applied Statistics* 41:337-348.

Gómez Cruz, M. A., L. Gómez Tovar and R. Schwentesius Rindermann (2002) Dinámica del mercado internacional de productos orgánicos y las perspectivas para México. *Momento Economico* 120, 54-68.

Gómez Tovar, L. and M. A. Gómez Cruz (2004) Latin America country reports: Mexico. In: *Organic Agriculture Worldwide: Statistics and Future Prospects* (M. Yusseffi and H. Willer, Eds.). pp. 137-139. Foundation Ecology and Agriculture (SOL) in collaboration with the International Federation for Organic Agriculture Movements (IFOAM).

Greene, W.H. (1997) *Econometric Analysis*, Upper Saddle River, NJ: Prentice Hall.

Ibrahim, J.G., M.-H. Chen, and D. Sinha (2001) *Bayesian Survival Analysis*, New York: Springer.

IFAD (2003) *The adoption of organic agriculture among small farmers in Latin America and the Caribbean*. Thematic Evaluation 1337. International Fund for Agricultural Development, Rome.

IFAD (2005) *Organic agriculture and poverty reduction in Asia: China and India focus*. Thematic Evaluation 1664. International Fund for Agricultural Development, Rome.

Kiefer, N. M. (1988) Economic duration data and hazard functions. *Journal of Economic Literature* 26, 646–679.

Lancaster, T. (1992) The Econometric Analysis of Transition Data. *Econometric Society Monographs.* Cambridge: Cambridge University Press.

Lohr, L. and L. Salomonsson (2000) Conversion subsidies for organic production: results from Sweden and lessons for the United States. *Agricultural Economics* 22(2), 133-146.

Marsh, R. and D. Runsten (2002). The organic produce niche market: can Mexican smallholders be stakeholders?. In: *Strategies for Resource Management, Production and Marketing in Rural Mexico* (G. Rodríguez and R. Snyder, Eds.). pp. 71-104. Lynne Rienner Publishers Inc, US.

Musshoff, O. and M. Odening (2005) *Adoption of organic farming: A positive real options analysis*. Paper presented at the 9th Annual International Conference on Real Options: Theory meets Practice, 22-25 June, Paris, France.

Leonard, P. (2005) *Latin America. In: The World of Organic Agriculture: Statistics and Emerging Trends* (H. Willer and M. Yusseffi, Eds.). pp. 123-148. Foundation Ecology and Agriculture (SOL) in collaboration with the International Federation for Organic Agriculture Movements (IFOAM).

Newey, W. K. and K. D. West (1987) A Simple, Positive-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55(3), 703-708.

OTA (2004) *OTA market overview: Mexican organic market*. Technical report. Laundry Consulting LLC. Commissioned through the Organic Trade Association by the Foreign Agricultural Service International Cooperation and Development Program.

Padel, S. (2001) Conversion to organic farming: A typical example of the diffusion of an innovation? *Sociologia Ruralis* 41, 40-61.

Pietola, K. S. and A. O. Lansink (2001) Farmer response to policies promoting organic farming technologies in Finland. *European Review of Agricultural Economics* 28(1), 1-15.

Rigby, D., T. Young and M. Burton (2001) The development of and prospects for organic farming in the UK. *Food Policy* 26(6), 599-613.

Willer, H. and M. Yussefi (2007) *The World of Organic Agriculture – Statistics and Emerging Trends 2007*. International Federation of Organic Agriculture Movements (IFOAM) DE-Bonn and Research Institute of Organic Agriculture (FiBL), CH-Frick.

Table 1: Summary statistics

Description	Conventional mean	Conventional std	Organic mean	Organic std
Time to organic certification (years)	38.09	15.99	26.27	15.23
Location 1	0.37	0.48	0.32	0.47
Location 2	0.30	0.46	0.16	0.37
Location 3	0.20	0.40	0.24	0.43
Location 4	0.11	0.31	0.14	0.35
Location 5	0.02	0.12	0.14	0.35
Ownership	0.92	0.27	0.86	0.35
Total farm size	7.43	10.44	8.56	7.09
Avocado ha	4.35	2.90	6.35	3.79
Heard of organic	0.83	0.38	1.00	0.00
Know organic	0.58	0.50	0.92	0.28
Talk with organic	0.32	0.47	0.84	0.37
Labour	0.40	0.88	0.84	1.17
Plan	0.40	0.49	0.59	0.50
Other crop	0.29	0.46	0.49	0.51
Animals	0.19	0.39	0.22	0.42
Other job	0.26	0.44	0.46	0.51
Remittances	0.12	0.32	0.00	0.00
Received credit	0.25	0.43	0.38	0.49
Information source: None	0.14	0.35	0.11	0.31
Agronomist	0.63	0.49	0.43	0.50
Associations	0.02	0.15	0.08	0.28
University	0.00	0.00	0.03	0.16
Sanidad Vegetal	0.05	0.23	0.03	0.16
Other producers	0.11	0.31	0.14	0.35
Publications	0.02	0.15	0.11	0.31
Membership	0.20	0.40	0.70	0.46
Age	54.35	14.22	51.46	12.86
Education	1.19	1.06	1.89	1.45
Family education	2.13	1.17	2.65	1.16
Export: US	0.19	0.43	0.41	0.55
Export: other	0.20	0.46	0.57	0.55
Frequency of info access: Credit	0.41	1.02	0.68	1.25
Management	1.95	1.06	1.84	0.96
Price	1.77	1.31	1.86	1.23
Number of censored observations	128.00	0.00	0.00	0.00
Number of failure times	37.00	0.00	0.00	0.00
Number of observations	165.00	0.00	0.00	0.00
Condition number of design matrix	1437.56	0.00	0.00	0.00
Condition number of normalized design matrix	60.17	0.00	0.00	0.00

	Model									
	Exponential		Weibull		Extreme Value		Log Normal		Gamma	
Parameter Definition	β	HPDI (95%)	β	HPDI (95%)	β	HPDI (95%)	β	HPDI (95%)	β	HPDI (95%)
Scale			2.38	(1.99 2.84)	0.11	(0.09 0.13)	2.28	(1.10 4.04)	3.88	(2.48 5.68)
Location 1	**-2.71**	(-5.07 -0.33)	**-3.91**	(-6.16 -1.8)	**-2.24**	(-4.45 -0.46)	**2.44**	(0.51 4.25)	**-2.34**	(-3.99 -0.78)
Location 2	**-3.96**	(-6.12 -1.59)	**-5.86**	(-8.26 -3.66)	**-4.16**	(-6.31 -2.12)	**3.23**	(1.26 5.12)	**-3.22**	(-4.64 -1.70)
Location 3	**-2.06**	(-4.15 -0.18)	**-3.60**	(-6.45 -1.75)	**-2.13**	(-4.37 -0.26)	**1.92**	(0.16 3.75)	**-1.98**	(-3.31 -0.52)
Location 4	-0.15	(-2.79 1.93)	-0.66	(-3.19 1.96)	0.16	(-2.19 2.32)	0.78	(-1.09 2.60)	-0.50	(-2.05 1.10)
Location 5	-2.17	(-4.88 0.38)	**-3.31**	(-5.36 -0.46)	-1.97	(-4.01 0.09)	**2.37**	(0.35 4.36)	**-2.34**	(-3.66 -0.77)
Ownership	**-1.98**	(-3.43 -0.77)	**-2.24**	(-3.21 -1.21)	**-2.27**	(-3.43 -1.04)	**1.45**	(0.23 2.71)	**-1.10**	(-1.84 -0.54)
Total farm size	-1.50	(-4.32 1.54)	-1.59	(-4.34 1.77)	-2.57	(-6.92 0.77)	-0.08	(-2.93 2.81)	-0.74	(-2.22 0.57)
Avocado ha	**-2.80**	(-5.64 -0.57)	**-3.83**	(-7.06 -1.26)	**-4.17**	(-6.64 -1.7)	**3.17**	(1.14 5.48)	**-2.83**	(-3.82 -1.93)
Heard of organic	1.59	(-0.68 3.18)	1.08	(-0.85 3.24)	**2.53**	(0.47 4.54)	-0.65	(-2.3 1.17)	**1.40**	(0.43 1.98)
Know organic	0.07	(-1.76 1.73)	-0.05	(-1.56 1.49)	-0.02	(-1.23 1.03)	-0.37	(-1.54 0.61)	0.09	(-0.56 0.70)
Talk with organic	**1.63**	(0.44 2.63)	**2.16**	(0.90 3.20)	**2.03**	(0.91 3.22)	**-1.06**	(-1.72 -0.42)	**0.98**	(0.59 1.39)
Labour	0.49	(-0.94 1.91)	0.76	(-1.00 2.46)	1.14	(-0.51 2.87)	-0.64	(-1.89 0.71)	**1.07**	(0.39 1.73)
Plan	-0.31	(-1.18 0.90)	-0.30	(-1.20 0.54)	-0.11	(-1.02 0.78)	-0.03	(-0.67 0.59)	-0.14	(-0.51 0.28)
Other crop	0.63	(-0.24 1.64)	**0.94**	(0.15 1.86)	**1.32**	(0.32 2.32)	-0.14	(-0.75 0.41)	0.16	(-0.17 0.60)
Animals	-0.19	(-1.54 0.87)	-0.54	(-2.05 0.57)	-0.37	(-1.83 0.92)	0.01	(-0.66 0.67)	0.00	(-0.54 0.52)
Other job	**0.62**	(0.02 1.24)	**0.75**	(0.04 1.52)	**0.79**	(0.10 1.47)	-0.41	(-0.86 0.02)	0.33	(-0.09 0.66)
Remittances	**-4.62**	(-7.40 -2.55)	**-4.69**	(-7.16 -2.48)	**-5.03**	(-8.53 -2.3)	**2.85**	(0.04 6.57)	**-1.98**	(-2.74 -1.09)

Received credit	**1.26** (0.06 2.24)	**1.50** (0.43 2.63)	**1.65** (0.48 2.81)	**-0.73** (-1.51 -0.01)	**0.89** (0.35 1.34)
Information source: None	-1.25 (-3.44 0.79)	**-2.05** (-4.01 -0.19)	-1.19 (-2.90 0.51)	0.40 (-1.30 2.33)	0.28 (-0.63 1.31)
Agronomist	**-1.95** (-3.25 -0.53)	**-2.84** (-4.13 -1.62)	**-2.71** (-3.95 -1.27)	**1.17** (0.14 2.27)	**-1.27** (-1.92 -0.57)
Producers' Associations	0.43 (-1.45 2.26)	0.85 (-0.82 2.61)	0.81 (-1.38 2.74)	-0.47 (-1.77 0.84)	0.15 (-0.68 1.26)
University	0.46 (-2.08 2.90)	0.91 (-1.68 3.39)	-0.48 (-3.10 2.02)	-0.30 (-2.08 1.55)	0.39 (-1.16 1.70)
Sanidad Vegetal	**-2.53** (-4.39 -0.34)	**-3.15** (-5.57 -0.91)	**-2.34** (-4.74 -0.46)	1.22 (-0.48 3.05)	**-1.54** (-2.55 -0.48)
Other producers	**-1.93** (-3.93 -0.40)	**-2.77** (-4.29 -1.15)	**-1.71** (-3.15 -0.07)	0.98 (-0.21 2.29)	**-0.87** (-1.84 -0.06)
Publications	**-2.31** (-3.84 -0.65)	**-3.43** (-5.22 -1.91)	**-2.88** (-4.44 -1.45)	**1.56** (0.34 2.72)	**-1.61** (-2.33 -0.83)
Membership	**2.46** (1.39 3.32)	**3.02** (2.05 4.08)	**3.26** (1.98 4.40)	**-1.49** (-2.17 -0.89)	**1.90** (1.56 2.27)
Age	**-3.20** (-5.51 -1.07)	**-6.54** (-9.09 -3.84)	**-7.04** (-9.71 -4.24)	**2.07** (0.37 3.74)	**-2.34** (-3.17 -1.03)
Education	0.89 (-0.73 2.45)	**1.61** (0.02 2.97)	**2.35** (1.13 3.89)	-0.84 (-1.87 0.21)	**1.06** (0.44 1.70)
Family education	-0.21 (-1.95 1.59)	-0.52 (-2.23 1.30)	-0.46 (-2.19 1.40)	-0.13 (-1.29 0.78)	-0.14 (-0.97 0.55)
Export: US	-0.03 (-1.38 1.13)	-0.50 (-1.75 0.96)	0.09 (-1.50 1.40)	0.23 (-0.80 1.25)	-0.40 (-1.00 0.38)
Export: other	**1.88** (0.66 3.30)	**2.43** (1.23 3.58)	**2.11** (0.59 3.67)	**-1.89** (-3.02 -0.75)	**1.49** (0.92 2.11)
Frequency of info access: Credit	-0.29 (-1.73 1.27)	-0.93 (-2.52 0.92)	-1.32 (-2.71 0.00)	-0.12 (-1.21 1.06)	-0.54 (-1.41 0.32)
Management	**-3.82** (-5.85 -2.08)	**-4.98** (-6.86 -3.15)	**-4.16** (-6.43 -2.30)	**2.56** (0.67 4.69)	**-1.49** (-2.32 -0.76)
Price	0.30 (-0.48 1.32)	0.42 (-0.62 1.37)	0.91 (-0.04 1.92)	-0.41 (-1.17 0.30)	0.34 (-0.28 0.73)
100k Log Maximum Likelihood	-176.17	-111.77	-156.92	-162.47	-154.06
Log Likelihood	-173.49	-112.64	-155.83	-160.83	-151.62
Log Marginal Likelihood	-215.69	**-153.54**	-174.51	-228.87	-199.15
Numerical Standard Error	0.30	0.33	1.70	0.52	1.01

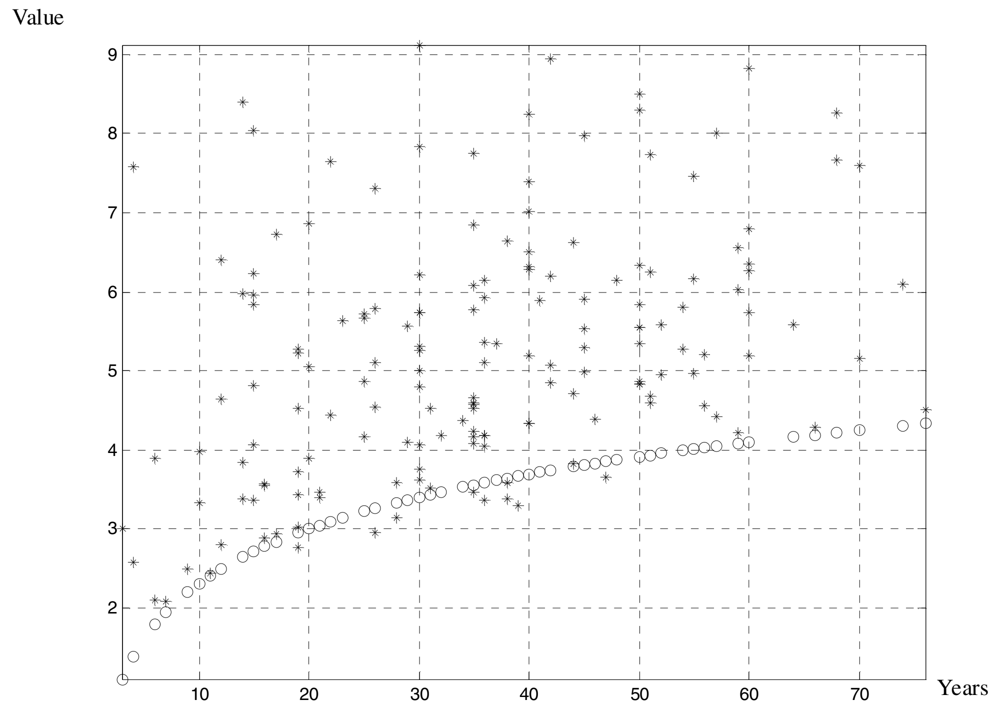

Figure 1. Predicted and observed duration times (log scale)

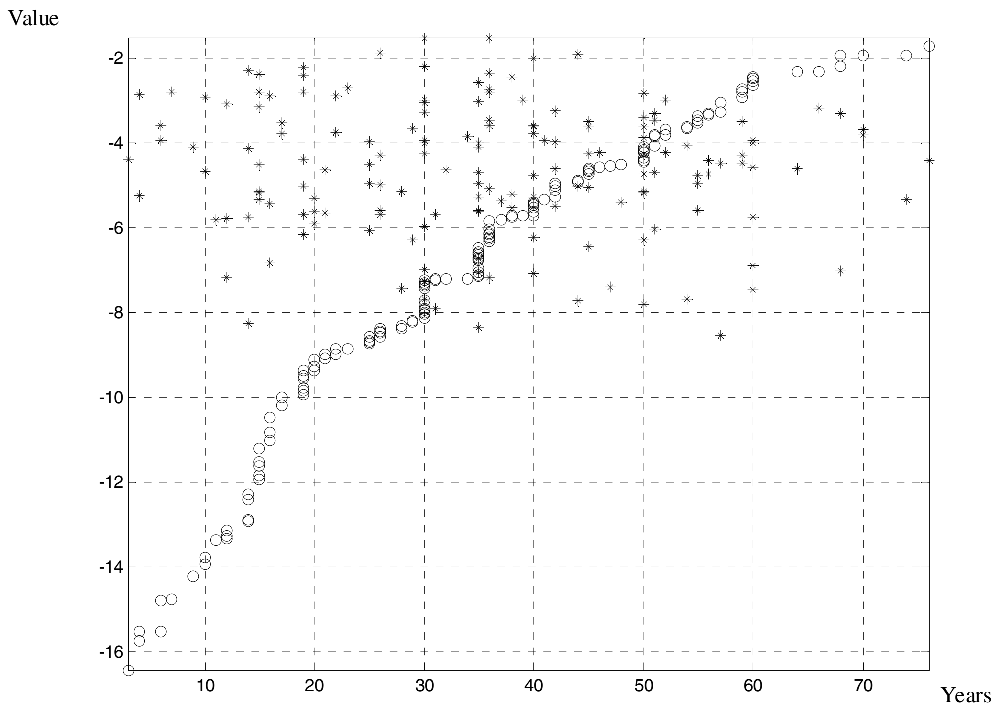

Figure 2. Predicted and actual hazards rates (log scale)

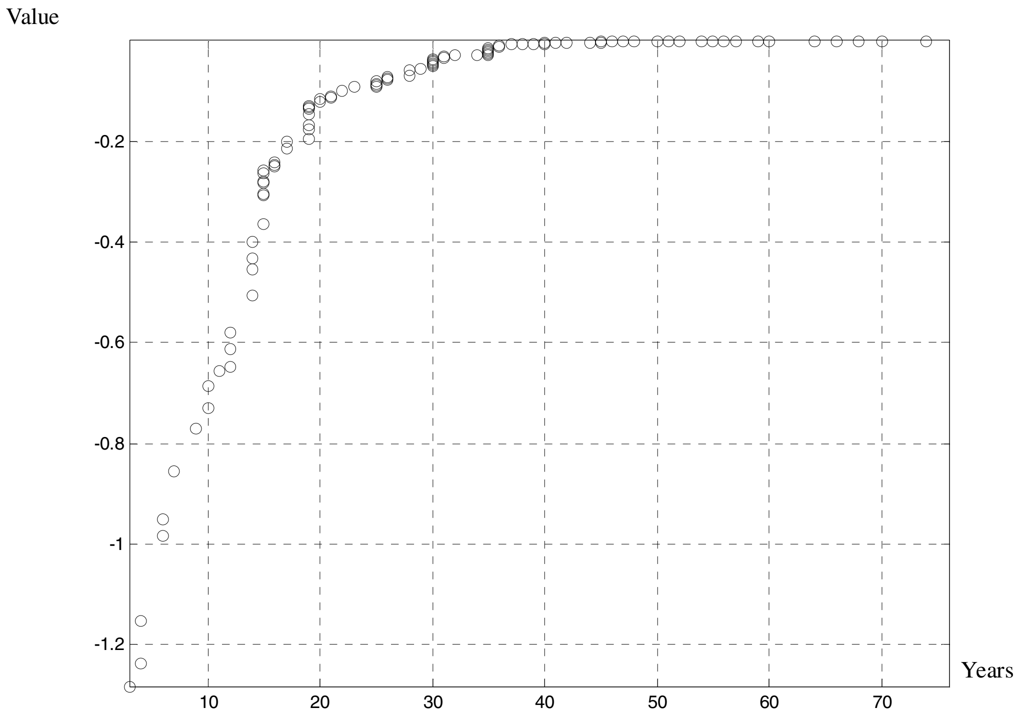

Figure 3. Predicted changes in hazard rates per unit change in information